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THESIS

**ANALYSIS TO SUPPORT HAZARDOUS WASTE
MANAGEMENT RE-ENGINEERING AT LAWRENCE
LIVERMORE NATIONAL LABORATORY**

by

Douglas A. McGoff

September 1997

Thesis Advisor:

Patricia Jacobs

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**ANALYSIS TO SUPPORT HAZARDOUS WASTE MANAGEMENT RE-
ENGINEERING AT LAWRENCE LIVERMORE NATIONAL LABORATORY**

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Lieutenant, United States Navy
BS, United States Naval Academy, 1990

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

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ABSTRACT

This thesis presents an analysis of the current hazardous waste management re-engineering project in progress at Lawrence Livermore National Laboratory (LLNL). The primary goal of the re-engineering is to streamline the hazardous waste storage infrastructure through the closure of a large number of existing storage facilities and utilizing a smaller number of "Consolidation" facilities. This goal is accomplished through both waste reduction efforts and early classification of wastes using a Waste Evaluation Form (WEF). Storage need is a function of the amount of waste generated and the time that those wastes remain in storage prior to disposal. Data analysis techniques are used to analyze the quantities of hazardous waste that have been generated at LLNL, as well as the amount of time that these wastes have traditionally remained in on-site storage facilities awaiting disposal. Mathematical and simulation models have been formulated to determine waste storage needs. The results of these models appear reasonable when compared with initial reports from re-engineering efforts being implemented at LLNL, and are used to form recommendations for further re-engineering efforts.

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EXECUTIVE SUMMARY

Lawrence Livermore National Laboratory (LLNL) is a U.S. Department of Energy (DOE) facility operated by the University of California. Through the process of conducting research, as well as normal maintenance of the facility, the facility produces a large quantity of hazardous, radioactive, and mixed wastes, which must be managed from generation to disposal in accordance with local, state, and federal regulations. LLNL has undertaken efforts over the past several years to decrease the quantity of hazardous materials being generated.

Recognizing that the hazardous waste storage infrastructure was designed during a period when a larger quantity of hazardous waste was being generated, LLNL contracted the consulting firm of Booz-Allen and Hamilton to conduct an assessment of hazardous waste management practices and make recommendations for a re-engineering of the waste management process. Utilizing this report, LLNL has undertaken a re-engineering effort designed to reduce the storage infrastructure by closing a large number of Waste Accumulation Areas (WAAs) and routing the waste from these facilities to a small number of Consolidation WAAs. The re-engineering effort also focuses on reducing the amount of time that wastes spend being serviced for off-site disposal shipments by utilizing a new Waste Evaluation Form (WEF) to classify the waste prior to entry into the Consolidation WAA.

The total quantity of material in storage is a function of the number (and size) of containers of waste being generated each week, as well as the amount of time that each

container must spend in storage being serviced for off-site shipment. Historical data of waste generation rates and service times have been analyzed and summarized.

Mathematical and simulation models have been formulated to study storage needs. The models incorporate aspects of what the hazardous waste re-engineering effort is expected to accomplish. The inputs to the models include waste generation rates and service times obtained from the data analysis. The primary focus of the models is determining the effect that hazardous waste pre-classification has on peak waste storage requirements at the Consolidation WAAs.

The broad qualitative behavior of the models is not unlike the reported experiences from initiatives already in progress at LLNL. Using the current estimates for time to perform waste servicing tasks under the re-engineered system and the percentage of material arriving for storage pre-classified by WEF, the simulation model suggests that the storage capacity designated to hold the hazardous waste may occasionally experience periods in which the storage capacity is exceeded. The risk of this occurring is deemed low, but will have to be weighed against the costs of such an occurrence.

I. INTRODUCTION

A. THE PROBLEM

Lawrence Livermore National Laboratory (LLNL) is a U.S. Department of Energy (DOE) facility operated by the University of California. It serves as a “national resource of scientific, technical, and engineering capabilities.” [LLNL Environmental Report 1995, pg. EX-1]. During the course of meeting its mission, it must maintain compliance with all local, state, and federal regulatory requirements. The Environmental Protection Department (EPD) of LLNL is responsible for “environmental monitoring and analysis, hazardous waste management, environmental restoration, and ensuring compliance with environmental laws and regulations.”[ibid.]

Over the past several years, LLNL has taken steps to reduce the quantities of hazardous wastes being generated by the various research activities associated with the laboratory. DOE established the goal that by 31 December 1999, the quantities of radioactive, low-level mixed, and hazardous wastes generated by routine operations were to be reduced by 50%, relative to quantities generated in 1993 (the baseline year); [LLNL Environmental Report 1995, pg. 3-6] Toward meeting this goal, LLNL has instituted several measures encouraging waste minimization efforts. The construction and implementation of the Chemical Exchange Warehouse (CHEW) now allows for the centralized storage and distribution of excess materials left over from one research activity, which may be used by another activity rather than being disposed of as waste. The use of reusable synthetic and semisynthetic coolants in machine shops, and various recycling initiatives also contribute to waste minimization efforts. These initiatives,

combined with other efforts to minimize the generation of hazardous wastes, have aided in reducing the overall waste quantities now being disposed by the lab. For example, approximately 1.7 million kilograms of hazardous wastes were generated in 1990, with only 334,000 kilograms of waste being generated in 1995. From 1994 to 1995 alone, hazardous waste generated was reduced by 27.8%. [LLNL Environmental Report 1995, pg. 3-9 to 3-10]. Additionally, DOE and LLNL selected 3 of 5 process waste streams that were the highest generators of waste (hazardous, low-level, and mixed wastes) and targeted these wastes for a 5% annual reduction in generated quantities starting in 1995.

Recognizing that reduced quantities of generated waste would no longer require the infrastructure that had been put in place to handle much larger quantities, LLNL recently contracted the consulting firm of Booz-Allen and Hamilton to conduct a review of the Laboratory's waste management program. This review detailed several areas where cost savings could be generated by altering current practices and procedures. The reduction of hazardous waste storage facilities was one procedure which was identified as resulting in significant cost savings. The study did not identify specific facilities to close, nor did it identify how much total storage infrastructure should be reduced, but rather noted that the existing capabilities to store wastes far exceeded the demand for that space. [Booz-Allen and Hamilton, 1996] Additionally, by reducing the amount of time that wastes required for processing, LLNL would be able reduce its reliance on long-term storage facilities. The results of this firm's report is being used as a basis for a re-engineering plan being implemented by the LLNL's Hazardous Waste Management (HWM) Division.

The federal, state, and local environmental regulatory requirements regarding the safe management of hazardous materials have been established primarily as safeguards to prevent damaging mishaps from occurring, and to minimize the effect of these mishaps should they occur. LLNL undergoes numerous inspections by regulatory agencies, and self-monitors, for compliance. Safety is, quite reasonably, the most important factor whenever a waste management program is under review and should never be sacrificed for increased efficiency or economy; the ramifications of following unsafe practices when handling or storing hazardous wastes can have dire consequences (toxic spills, fire, etc.). With this in mind, it is the waste manager's goal to improve efficiency and economy of operations without sacrificing safety.

B. THESIS OBJECTIVE

This thesis discusses several key initiatives being incorporated under the LLNL HWM re-engineering effort. Statistical analysis and inventory control methodology are used to determine the impact of these initiatives on total waste storage capacity utilization, primarily to determine the feasibility of planned Waste Accumulation Area (WAA) closures and the benefits associated with further restructuring. Specifically, the disposal process for hazardous wastes is modeled as an inventory control process with waste storage space as the commodity in demand. Utilizing this frame of reference, the waste minimization efforts currently in effect should allow for a forecast of future demand for storage space no greater than that needed by current or previous demands.

The two primary factors that affect the inventory levels of hazardous wastes at LLNL are the quantities of waste being generated and the amount of time that the waste is

stored. Each WAA that is closed will transfer its generators' demand for storage space (the generated waste) to a "Consolidation" WAA.

A mathematical model is developed to estimate the long run average inventory level at each Consolidation WAA. This long run average serves two purposes; to gain an understanding of the effect of various initiatives on the inventory levels and to verify that the simulation, described later, is behaving as designed.

Using simulation, the current waste management practices are applied to the quantities of generated waste, modeled through data analysis of previous disposals; this model examines the feasibility of WAA closures currently planned under the LLNL HWM reengineering plan under "Old" management practices. In essence, this model acts as a baseline for comparison with the results obtained by further efforts at expediting waste disposal. The model should be considered as an assessment of the possibility of reducing storage infrastructure without changing any procedural practices.

The second model allows the HWM managers to apply the results of pilot program efforts and goals in expediting preparation of waste for disposal to determine the effect that these initiatives have on inventory levels. This model simulates the waste disposal process under the re-engineered processes to assist in the determination of storage space requirements. This model utilizes waste generation rates, processing times, and other factors noted in the model description, that are input into the model. This model gives the waste manager an idea of what effect future initiatives may have on his needs for storage space. The primary focus of the model is in determining the effect that pre-classifying wastes at the point of generation, through the use of the Waste Evaluation Form (WEF), has on peak inventory levels at the Consolidation WAAs.

C. RESEARCH QUESTIONS

As part of the objective, this thesis seeks answers to the following questions:

1. What practices and procedures have been used in the past to handle wastes?
2. Can these procedures be successfully applied to the current, and future, declining volumes of waste while only changing the number of storage facilities ?
3. What costs are expected to be averted by changing the processes for handling wastes under re-engineering, and what initial expenditures will be required to bring the system into the new standards?
4. How would the new waste handling system affect short and long term costs?
5. How does the new waste storage system affect storage requirements, and how sensitive would the new system be to changes in demand or waste processing time ?

D. SCOPE OF THE STUDY

The thesis focuses on the current and future initiatives for hazardous waste storage and transfer at the Lawrence Livermore National Laboratories. Two approaches to modeling these initiatives are discussed. A mathematical model is used to determine a point estimate for the long run average waste storage level that would be expected under various conditions. Additionally, a simulation model is developed to give information beyond this point estimate, predicting probable peak waste storage levels, at defined levels of risk (high quantiles of the distribution for waste storage level), over a period of time. For each type of model, we first utilize data from previous waste disposal activities by

WAAs scheduled for closure, as well as the time that was required to dispose of that waste, to determine a maximum amount of storage space that would be required under the “old” system, and whether or not the designated consolidation point would be able to handle that volume. We then model key aspects of the hazardous waste generation and handling process under assumptions of what the re-engineering effort is expected to accomplish.

The re-engineered waste handling process places additional tasks on the Consolidation WAA which had been performed at the long term storage facilities under the “Old” system. The effect of these additional tasks would be additional time to process wastes within the Consolidation WAA if all other factors remained the same. Through implementing the pre-classification process (WEF), some percentage of the waste entering the Consolidation WAA will require very little processing. The higher the percentage of waste that is pre-classified, the greater the savings in total processing time in the facility. This savings in time has a direct effect on the resulting inventory level of the facilities, since the waste can be shipped out much more quickly. However, if the percentage of waste being pre-classified is too low, the additional time to perform the tasks of the long term facility will cause inventory levels to be higher than levels under the “Old” system, and therefore the re-engineering will not allow for as many facility closures as a restructuring under “Old” management practices would have.

E. METHODOLOGY

This study began with a six week experience tour visit to LLNL in November and December of 1996. This visit allowed for observation of waste handling and storage

operations, as well as discussion with personnel involved with the re-engineering process about what the goals and expectations of the process were. I was allowed access to all available documents, and given freedom to determine where I felt further analysis could be applied. It was obvious that data on all aspects of the hazardous waste generation, storage, and disposal process was readily available, because the “cradle to grave” tracking of wastes required by federal hazardous waste regulations has been continuously in effect. I was also able to attend a Total Waste Management System (TWMS) training class. TWMS is a relational data base that contains all of the waste tracking information, and can be queried for reports of many types.

The data available from TWMS can be queried by data field, for example to find the date the waste was generated, the size of the container, or the waste codes assigned. By working with sample sets of hazardous waste data, I noted that while many of the individual WAAs scheduled for closure had processed few containers of waste over a period of time, the combination of the amounts of wastes from several of the closing WAAs became quite sizable.

Having ample opportunity to speak with personnel involved, I noted that it would be beneficial to simulate the waste management process to get an understanding of the effects of the re-engineering process on waste inventory levels, and validate the feasibility of closing certain WAAs. Additionally, developing a simulation model for the waste management system would allow for testing the effect of changes in the system without incurring the cost or disruption associated with actually incorporating the change. A model allows the manager to ask “what if” questions regarding various portions of the waste handling process and get a better idea of the effect a change could have on the

system as a whole. As mentioned previously, the goal is to ensure feasibility of the new process, and ensure that the closures of various WAAs would not overload the Consolidation WAA to which it is planned to route and store the waste. Additionally, if the model indicated that the remaining capacity was sufficient to accommodate the waste from a WAA not scheduled for closure, future closures could be investigated.

The factors affecting the total amount of hazardous waste in inventory at any given moment are fairly straight forward. Containers of waste arrive each week and each item must be stored while the paperwork, repackaging, labeling, testing, etc., required for shipment is completed. Once these matters are taken care of, the waste is ready for manifesting for an off-site shipment, but may be held while more material is accumulated to ensure that the shipment vehicle will be more fully utilized. Accumulation to maximum vehicle capacity may not always be an option, since waste can be in a WAA facility for at most 90 days, and advance notice is required for a truck to come and pick up a shipment on a given date.

The TWMS database maintains an account of how much waste has been produced each week, as well as the amount of time that the waste was stored in a WAA under the “old” system. Additionally, technicians at LLNL are able to provide information regarding the time that is required for various functions that were performed on the waste at the Treatment, Storage, and Disposal Facility (TSDF), which will now be performed at the Consolidation WAA, such as random chemical analysis spot checks and manifesting for off site shipment.

Additionally, it should be mentioned that the time to handle each waste disposal may change when wastes are coming from various sources and when the total weekly

volume of diverted waste all arrive at one place. These matters are considered under the modeling assumptions for each model.

The data analysis portion of this thesis presents the results of summarizing the data received from TWMS into a form conducive to analysis, as well as the results of using common distributions to summarize the data for use in the simulation models. Data analysis was performed utilizing two commercially available software packages: S-Plus [Version 3.3 for Windows, StatSci, 1995] and the ARENA [Version 2.2, Systems Modeling Corporation, 1992-1996] Input Analyzer.

F. DEFINITION OF TERMS

Presented here are a few terms that pertain to the problem statement

- **Hazardous Material :** Hazardous material(s) “is a broad term encompassing any material, including substances and wastes, that may pose an unreasonable risk to health, safety, property, or the environment, when they exist in certain quantities and forms.” [The Comprehensive Handbook of Hazardous Materials, intro.]
- **Hazardous Waste :** “discarded materials that pose a risk to human health, safety, property, or the environment.” [The Comprehensive Handbook of Hazardous Materials] “Wastes exhibiting any of the following characteristics: ignitability, corrosivity, reactivity, or EP-toxicity (yielding toxic constituents in a leaching test). In addition, EPA has listed as hazardous other wastes that do not necessarily exhibit these characteristics.” [LLNL Environmental Report 1995, pg. G-14] A hazardous material becomes a hazardous waste when it is directed to be disposed of, or “generated” (see below), whether it has been used or not.
- **Radioactive Waste :** While the term radioactive waste should be sufficiently descriptive to explain its meaning, it is important to note that there are varying degrees of radioactivity. Low-level Radioactive Waste is defined as waste with a transuranic nuclide concentrations less than 100nCi / gram. Transuranic (TRU) Waste is material contaminated with alpha-emitting transuranium nuclides, which has an atomic number greater than 92, half life longer than 20 years, and is present in concentrations greater than 100 nCi / gram of waste. “Radioisotopes that give off alpha radiation are generally not health hazards unless they get inside the body through an open wound or

are ingested or inhaled. In those cases, alpha radiation can be especially damaging.”

[LLNL Environmental Report, 1995]

- **Mixed Waste** : waste that has the properties of both hazardous and radioactive waste.
- **Waste Generator** : any activity which results in the creation of a waste which must be disposed of. Typically, at LLNL a “Generator” is either a research or maintenance facility.
- **HWM** : Hazardous Waste Management Division of the Environmental Protection Department at LLNL.
- **WAA** : Waste Accumulation Area. An officially designated area that meets current environmental standards and guidelines for temporary (less than 90 days) storage of hazardous waste before pickup by the Hazardous Waste Management Division for off-site disposal.
- **WPAA** : Workplace Accumulation Area. An area within the workplace with a container designated for the accumulation of waste. LLNL policy dictates that waste may accumulate within the workplace for no more than 9 months from start of filling a container before the container must be sealed and removed from the workplace.
- **TSDF** : Treatment, Storage, and Disposal Facility; A facility that operates under the guidelines of a permit granted by the EPA for storage and handling of specific wastes.
- **ORAD** : Operations and Regulatory Affairs Division of the Environmental Protection Division at LLNL.

II. HAZARDOUS WASTE MANAGEMENT AT LLNL

A. BACKGROUND

In December, 1970, the Environmental Protection Agency (EPA) was created. At the time, the agency was formed as part of a series of reforms designed to promote worker safety. “For the most part, hazardous materials were not considered to be a public nuisance or an environmental health concern” in December of 1970 [Comprehensive Handbook of Hazardous Materials, pg.6]. During the same month, the Occupational Safety and Health Act was implemented “to assure safe and healthful employment conditions for all men and women working in the U.S.” [ibid, pg. 8] and brought about the establishment of the Occupational Safety and Health Administration (OSHA). The formation of these two federal agencies resulted in nationwide regulations, standards, and requirements for personal and environmental health issues.

Since the establishment of these federal agencies, the volume of federal environmental regulations has jumped dramatically. The most significant regulations regarding the handling of hazardous materials can be found in the Toxic Substances Control Act of 1976 (TSCA) , which granted EPA “broad regulatory authority over most chemical substances,” [ibid, pg. 31] and the Resource Conservation and Recovery Act (RCRA), passed on October 21, 1976 but not enacted until 1986, which established the guidelines for hazardous waste classification, cradle-to-grave manifesting, standards for generators, transporters and facilities which treat, store, or dispose of hazardous waste, enforcement of these directives through a permitting program, and authorized state

programs to operate in lieu of federal programs (these wastes are called non-RCRA hazardous wastes, or “California only” wastes for our purposes). [ibid, pg. 35]

B. THE SYSTEM BEFORE RE-ENGINEERING

LLNL, like all high volume hazardous waste generators, must conform to the standards and regulations established by federal, state, and local authorities. The financial penalties for failure to do so, and the actual hazards that may result from non-compliance, are severe. The flow of waste can be viewed as a four stage process, as shown in Figure 1.1. (Shown below)

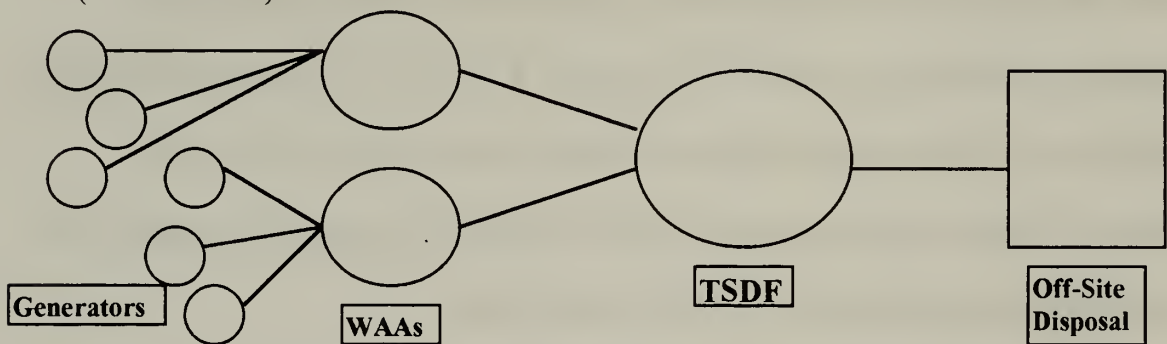


Figure 1.1

The procedure for handling wastes has been as follows:

1. Several hundred “generators” conduct research, maintenance, etc. creating hazardous wastes which must be disposed of. These wastes may be radioactive waste, non-radioactive (“traditional”) hazardous waste, or mixed waste (both hazardous and radioactive). Federal and State regulations regarding the handling of radioactive wastes are separate from those laws regarding “traditional” hazardous wastes.
2. Generators are limited (by law) to holding wastes in their laboratory, work site, etc. to a period of 1 year from start of filling a container (first drop in), or until the container that holds the waste is full, whichever occurs first. LLNL keeps this period at 9

months or less. Often, wastes are turned in earlier (i.e. - when the experiment generating the waste ends, or just to get the hazard out of the workplace sooner.) In general, many types of containers have been used with the waste then repackaged into DOT approved containers at the WAA. For solid lab trash, for example, a garbage bag could be considered an accumulation container, but would not be approved for transporting that waste. This container would be placed within an approved container (over-packed) for shipment.

3. When wastes leave the workplace, they are picked up by HWM or hand carried by the generator and delivered to the closest Waste Accumulation Area (WAA) able to accept that waste (there are 39 WAAs lab wide). Some generators have their “own” WAA, generally a small Chemical Storage (Chem-Stor) building or shed, located outside the generator’s building. There are many laws regarding how items may be stored at a WAA (segregation of incompatible wastes, aisle requirements, stacking limitations, spill abatement, etc.) but there are significantly fewer restrictions regarding the types of waste which may be stored in a WAA than there are for a Treatment, Storage, and Disposal Facility (TSDF).
4. Hazardous wastes are allowed (by law) to remain in a WAA for up to 90 days pending transfer to an approved (and licensed) TSDF or off-site disposal facility. If this requirement will be exceeded (i.e. - the waste cannot be accepted into one of the laboratory’s TSDFs or disposed of off-site within 90 days) a letter must be written to the State of California describing the circumstances, and a fine for non-compliance may be issued against LLNL.

5. During these 90 days, the hazardous wastes are properly identified, chemical analysis performed to categorize the waste, and the material is otherwise prepared for transfer to a TSDF. A RCRA permitted TSDF can only accept wastes that have been completely classified and containerized for storage. The on-site TSDF traditionally coordinates all off-site transfers of wastes. If the waste cannot be brought into the TSDF, then the waste is transferred to an off-site disposal facility straight from the WAA.
6. Upon transfer to a TSDF (permitted facility maintained at LLNL), the hazardous waste can be stored for up to 1 year while disposal is arranged. Only extraordinary conditions would require wastes to be stored in excess of the one year limit, and again the state would have to be notified if this were to occur (possibly resulting in stiff fines for non-compliance). Most wastes are readily identified as having an approved disposal company associated with that waste type, but the amount of time waste spends at the TSDF has traditionally not been a focus of concern. LLNL maintains 4 TSDFs, which are each permitted by the State of California to handle various specific waste types. If a waste is generated on the laboratory facility that is not covered by the TSDF's Part B RCRA permit, it must be shipped off site from a WAA.
7. Radioactive and mixed wastes are also stored at existing TSDFs, and are separated from the hazardous waste. The amount of time that radioactive wastes may be stored, either at a TSDF or in a WAA, is determined by Department of Energy policy and is separate from the regulations regarding hazardous and mixed wastes, but timely transfers and disposal are desired. Mixed waste storage is regulated under a "Site Treatment Plan," an agreement between DOE and the Department of Toxic

Substances Control (DTSC), and often the characteristics of the mixed waste dictates that it must be stored in a hazardous waste storage cell (decreasing available storage space) while awaiting treatment or off-site transfer.

8. No hazardous wastes are “disposed” at LLNL, but some wastes are treated (through an approved procedure) to a non-hazardous, or less hazardous, state on-site. Off-site disposal companies have numerous ways of treating wastes, and can sometimes dispose of wastes by incineration or by recycling processes. Although the waste treatment procedure is considered when deciding where to ship a waste for disposal (i.e. - recycling is a politically superior alternative), end price of disposal (including shipping costs) is currently the primary consideration.

C. THE MOVE TOWARD RE-ENGINEERING

LLNL has been making efforts to reduce the amounts of hazardous and mixed wastes being generated through various waste minimization programs, and has been largely successful in these efforts. As a result, LLNL contracted with the consulting firm of Booz-Allen and Hamilton to review these waste handling practices and determine areas that could be re-engineered to affect cost savings. The firm published their final report in February of 1996. It contained several broad recommendations that have acted as a basis for LLNL’s HWM Division’s re-engineering effort. [Booz-Allen and Hamilton, 1996]

Utilizing the February ‘96 Booz-Allen and Hamilton Report as a guideline, the re-engineering effort focused on several key issues. Specifically, if hazardous waste can be properly classified and readied for shipment within 90 days, the need for an on-site RCRA permitted TSDF is reduced. [ibid, pg. 23] One possible procedure is to classify the

hazardous wastes early in the disposal process, and transfer the wastes into a WAA in DOT approved containers, and thereby have the wastes virtually ready for shipment when they enter the WAA. [ibid, pg. 18-21] Since there is less waste being generated, and each waste element spends less time in storage, then smaller storage capacity is required. Hence a number of the existing storage facilities can be closed, and the wastes would go to a smaller number of “Consolidation WAAs.” The storage and handling of radioactive wastes does not change significantly.

The flow of wastes under the re-engineered process can be seen as a three stage process, shown as Figure 1.2.

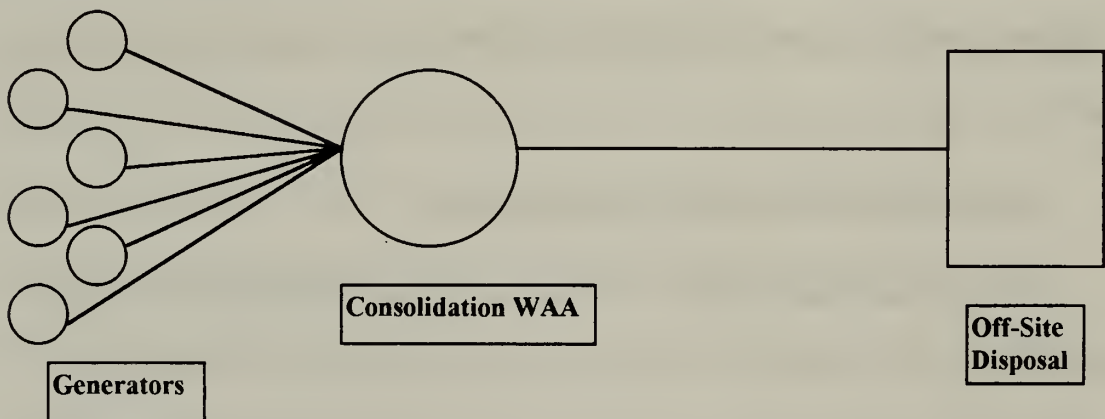


Figure 1.2.

The re-engineered process is as follows:

1. A generator that requires disposal for a waste that he has generated notifies HWM of the need for disposal. The generator has accumulated this waste in a Department of Transportation (DOT) approved hazardous waste container.
2. If the generator has generated the same waste in the past, he already has the proper classification recorded on a Waste Evaluation Form (WEF). If it is a waste type not previously disposed of by that generator, the generator uses his own experience with how the waste was generated and what materials are in the container based on the research he was performing to identify the waste constituents and classify the waste appropriately. This is called using "Process Knowledge." If the generator requires assistance in classifying the waste, he can contact the HWM Division which provides him with a field technician team to assist in the classification of the waste. A random sampling of wastes is performed later in the service process to determine if wastes have been misclassified. Misclassification can have serious safety implications, as well as financial penalties if discovered after the waste leaves site. Thus, if there is any doubt the waste is treated with a "worst case" concern for what may have been generated until chemical analysis proves otherwise.
3. If the generator and field technician team are unable to completely classify the waste, a sample of the waste is chemically analyzed to determine classification, utilizing what knowledge is available on the waste as a basis for further testing. If further testing is not economically feasible, the waste must be disposed of with a "worst case" classification based on the process that generated it.

4. Once classified properly, the waste is labeled and transferred to the “Consolidation” WAA designated for that generator’s waste. The WAA is typically decided by proximity to the generator, or to a specialty WAA designated for the collection of the particular waste form (i.e. - batteries, PCB containing materials, explosives, etc.). At this point, the 90 day limit for WAA storage is set.
5. While in the WAA, the waste is checked for proper labeling and the process of manifesting the waste to an upcoming disposal pickup begins.
6. When all validation checks have been completed on the waste and random chemical analysis spot-checks have been performed, the waste is identified as ready for manifesting for pickup and disposal.
7. When ample wastes have accumulated lab wide to warrant a shipment, or when any wastes approach their 90 day limit for storage in the WAA, available containers are manifested to an appropriate off-site disposal facility.
8. When the disposal facility has had time to review the manifest and schedule pick-up of the waste, HWM Division is then notified of the date that the material is scheduled for pickup.
9. On the day of pickup, or the day before depending on the size of the shipment, all designated containers are prestaged at assigned pick up locations and readied for transfer.

While the Booz-Allen and Hamilton report did not identify specific facilities to target for consolidation / closure, the Hazardous Waste Management Division has decided on a number of facilities that are candidates for consolidation / closure. Table 2-1 lists the

facilities currently under consideration for consolidation, or in process of being closed, as well as the facilities designated as Consolidation WAAs. The list is complete as of 05 August 1997, and includes some modifications from the list originally provided during my experience tour during November and December of 1996. The waste containers that have traditionally been routed to the listed facilities will instead be delivered to a Consolidation WAA for processing. The number of containers being stored in the Consolidation WAAs will therefore be the sum of the containers that would have been stored in the listed facilities, as well as those items that originally went directly to the (now called) Consolidation WAA(s). The table lists closing facilities by zone, followed by the facilities designated to receive all of the consolidated waste.

Consolidations and Closures		
Zone	WAA	ORAD Capacity
1	406	(3) 55 gallon drums
	412	(9) 55 gallon drums and (10) lard cans
	431	(12) 55 gallon drums and (20) lard cans
	511	(60) 55 gallon drums
	519	(12) 55 gallon drums
	611	(12) 55 gallon drums
	691	(8) 55 gallon drums
	5125	(12) 55 gallon drums
	551W	(24) 55 gallon drums
1	TOTAL	(152) 55 gallon drums and (30) lard cans
2	254	(5) 55 gallon drums and (15) lard cans
2	TOTAL	(5) 55 gallon drums and (15) lard cans
3	191C	(12) 55 gallon drums
	197	(50) 5 gallon carboys
3	TOTAL	(12) 55 gallon drums and (50) 5 gallon carboys
4	121	(14) 55 gallon drums
	131B	(10) 55 gallon drums
	227	(110) 5 gallon carboys
	231	(20) 55 gallon drums
	235	(12) 55 gallon drums
	241	(20) 55 gallon drums
	251	(12) 55 gallon drums
	253	(10) 55 gallon drums
	261A	(8) 55 gallon drums
	331	(12) 55 gallon drums
	341	(10) 55 gallon drums
	322B	(20) 55 gallon drums
4	TOTAL	(148) 55 gallon drums and (110) 5 gallon carboys
Consolidation Facilities	612-4*	Various cells, total capacity (736) 55 gallon drums
	169	(52) 55 gallon drums
	361	(16) 55 gallon drums, (40) 7 gallon containers
Consolidation	TOTAL	(804) 55 gallon drums, (40) 7 gallon containers

Table 2-1.

* Facility 612-4 is currently a RCRA permitted facility. This means that all waste must be properly containerized and characterized prior to entering this facility.

D. CONCLUSION

One of the key elements of the re-engineering plan is getting the waste ready for off-site disposal as quickly as possible. By performing the majority of these functions before the 90 day WAA storage time begins, the waste will spend significantly less time in the facility than under current procedures. This is to be accomplished through the use of the WEF. The greater the percentage of waste that can be classified through use of a WEF, the greater the decrease in total time required to service the waste. Additionally, if all wastes can be classified within 90 days, there will no longer be a need to maintain facility 612-4 as a RCRA permitted facility.

If the amount of waste being generated decreases, and the amount of time that each item of waste spends in a storage facility also decreases, it should be obvious that less total storage capacity will be required. However, the question remains of what the new storage requirement will be under the re-engineering plan and what effect changes in the generated quantities or processing time would have on the amount of storage capacity required.

In the following chapters we examine the waste disposal data that are available for analysis, formulate models of the system, and then present results from the models.

III. DATA ANALYSIS OF GENERATED WASTES

A. DETERMINATION OF A UNIT OF STORAGE SPACE

In this subsection, the measurement unit of arriving waste is determined to study storage space requirements.

Regardless of the amount of waste that is in a container, it is the size of the container itself that dictates the amount of space needed for its storage. The number of waste containers that can be stored in a facility depends on floor space and the way that pallets can be placed to make use of that floor space. Pallet arrangements must be planned that maintain ample space for free movement around the pallets while maintaining physical separation of incompatible waste types. Typically, pallets are arranged in rows with space left between the rows wide enough for a stretcher to be brought down the alleyway in the case of a personnel injury, or with a central alleyway that allows for a forklift to travel between rows.

The total amount of liquids that can be stored in a facility is regulated, based upon the facility's ability to contain a spill; this requirement is derived by computing a percentage of the total number of drums that could be stored in the facility that may leak simultaneously and building into the facility a mechanism to contain that sized spill, such as a berm or a drain system.

The types of waste, as well as the exact sizes and maximum number of containers, that can be stored in the LLNL RCRA permitted storage facilities are described in Appendix 14.1 of the LLNL RCRA Part B Permit Application / Volumes 15-36 (see example in Appendix D). For each facility, there is a listed "Room Capacity" or "Cell

Capacity” which is the maximum number of gallons of liquid material that can be stored in that space. There is an “Allowed Number of Containers” which is the “Cell Capacity” divided by the Container Size, and rounded down to the nearest whole number. Also, there is an “Operating Number of Containers” which is based on space, rather than liquid volume, constraints for storage. The “Operating Number of Containers” is always no greater than the “Allowed Number of Containers” and is the limiting constraint on waste storage in a facility.

The way that the “Operating Number of Containers” is computed is based on how many pallets of material can fit in the facility under the storage site’s “Container Arrangement Plan” and the number of containers of a given size that will fit on a pallet. For simplicity, it is assumed that all containers of less than 10 gallon capacity take up the same amount of space, and that 12 of these small containers will fit on a standard 4ft. by 4 ft. pallet. Additionally, containers of 10 gallon to 85 gallon capacity take up roughly equivalent amounts of space (other than height), and 4 of these large containers will fit on a standard 4 ft. by 4 ft. pallet. Some storage areas allow for pallets to be stacked 2 high, with all the containers on the bottom pallet being the same size, and at least as large as the containers on top (common sense also dictates putting very heavy containers of waste, such as sand blast grit, on the bottom). Half-pallets, which are 2 ft. by 4 ft., can also be stacked 2 high, with the top half-pallet typically able to hold the same capacity as the bottom half-pallet. The exception to this is that only one 55 gallon drum can be placed on the top of a stacking of half pallets. Typically, storage areas will contain a mix of container sizes, and the combinations of containers and stacking arrangements are directed toward maximum utilization of space, when storage space is limited, or toward ease of

movement of drums when the cell is well below capacity. When possible, double stacking is avoided since it makes movement or inspection of a drum on the bottom stack more time consuming and manpower intensive.

For example, Area 612-4, Cell A, has a container arrangement plan that calls for (16) standard 4' by 4' pallets and (8) 2' by 4' half pallets on the floor. With this arrangement, we have a total storage capacity of (40) standard pallets, 16 double stacked standard pallets and 8 double stacked half pallets. If we were to have all 55 gallon drums (large drums), we could put 4 on each standard pallet, top and bottom, 2 on each bottom half pallet, and 1 on each top half pallet, for a total of 152 drums. It would be extremely rare, however, to have an entire storage space filled with 55 gallon drums, so this possibility is not likely to occur. If we were to instead have all 5 gallon containers, we could have 12 per standard pallet, top and bottom, and 6 per half pallet, top and bottom, for a total of 480 containers. Likewise, a mix of 240 small containers and 80 large containers is possible.

By viewing this 3 for 1 trade off between small drums and large, it is apparent that a common unit of measure between various drum sizes would simplify storage space approximations. This common unit of measure will here after be designated as the "5 gallon container equivalent" or "5GCE." Small containers require one 5GCE of storage space, while large containers require three 5GCEs of storage space. With large numbers of containers, it can be observed that a mixing of large containers and small may drive a need for reorganization within a storage cell during actual operations to ensure optimal use of space, but mixing storage containers does not adversely affect the analysis of remaining storage capacity. When dealing with only a few containers, the mixing of

different sized containers has greater effect; however it is obvious that storage space is not a critical factor in this case because total wastes in storage would be small compared to available space.

B. THE EFFECTS OF WASTE MINIMIZATION

By considering waste storage needs as a function of containers rather than waste volume, the effect of decreasing volumes of waste being generated no longer implies a direct relationship with storage space requirements. For example, suppose 5000 gallons of waste liquids produced by a facility were disposed as (100) 55 gallon containers (each containing 50 gallons of waste). If we could now reduce the waste produced by 20% less volume (4000 gallons of waste), we may see (80) 55 gallon containers (each containing 50 gallons of waste), or (60) 55 gallon containers (each containing 50 gallons of waste) and (40) 30 gallon containers (each containing 25 gallons of waste). Since a 55 gallon drum and a 30 gallon drum take up essentially the same amount of “Operating” storage capacity, in this case there would be virtually no change in storage capacity requirements at all. We will assume that decreasing waste generation will not lead to an increase in storage needs; data analysis is used to examine the reasonableness of this assumption.

The reengineering project is being implemented lab wide, but the consolidation of facilities has been divided into four distinct, non-overlapping “zones.” Data analysis is performed on each zone separately. The decision that determined what constituted a zone was based on a number of factors, including security requirements for portions of the LLNL facility complex, geographic separation of various storage facilities, and the current physical status of the facilities themselves (since consolidation of facilities also occurs by

zone). Security areas are designated as “Red” or “Green” areas, based on what color badge is required for personnel to enter that area. (Although it may seem counterintuitive, a “Red” security zone is less strictly controlled than a “Green” security zone. A good way to remember which area is higher security is that a person with a “Red” identification badge would have to STOP at the “Green” security perimeter, while a person with a “Green” security badge may GO into whichever area they want.) LLNL is a one square mile facility, and the primary goals of separating the laboratory into these zones was to ensure security when allowing transporters access to the waste, and ensuring that generated waste would not have to be transported over great distances to a storage site. Waste is typically transported by loading it onto a flatbed truck; however, if the storage site is in close proximity to the generation site, a forklift may be used for direct transport.

The roads on the LLNL facility are not public roads, and therefore some of the laws regarding the transportation of hazardous wastes on public roads do not apply for on-site transfer activities. LLNL Hazardous Waste Management Division does maintain some vehicles and drivers that are licensed to carry out off-site shipment, but this is not required for all vehicles.

C. A DISCUSSION OF DATA ANALYSIS TECHNIQUES USED

1. The Waste Arrival Process

The generation of wastes places a demand for space in storage facilities. There are several mathematical methods that can be used to forecast future demand, when ample

data on past demand are available. The data made available from LLNL was complete and spanned the entire life cycle of wastes for a number of years. This analysis was confined to the most recent two years worth of data. This analysis forms the basis of the storage demand forecasting contained in this thesis.

There are many analytical methods that may be used to model the arrival process and the demand for waste storage space. One such technique is to use the statistical average of the amount of waste to arrive over the entire time period in question as a single point estimate. This is frequently referred to as the naïve estimate, because it does not attempt to explain the variability of what is occurring, but rather just assumes that the entire period in question can be explained by a single number. While naïve, this estimate frequently does capture the overall effects of what is occurring, especially when there is no true change in mean demand. Additionally, this point estimate makes further calculations quite simple.

Probably the most frequently used tool for modeling demand is some form of time series analysis. “Time series analysis predicts the future from past data.” [Tersine, pg. 44] The typical method for applying time series analysis is to plot the demand data over time and see if there are visual clues that can aid the analyst in determining the effect of time on demand. Once data are plotted, the data are modeled as a combination of several components. “Time series analysis may contain up to five interactive components - levels, trends, seasonal variations, cyclical variations, and random variations.” [ibid.] While any or all of these components may affect the demand model, only trend, seasonality (also called time of year effect) and random variation will be considered in this analysis. For any of these components, the fact that they are present does not necessarily dictate that

their effect should be included in the final forecasting model. If the effect is so slight that it does not aid the decision maker in his forecast, and rather only adds complexity to the model, it should be ignored.

The trend component “identifies the rate of growth or decline of a series over time.” [Tersine] We will consider only linear trends. This means that a decreasing demand will be modeled by a trend line with a negative slope and increasing demand will be modeled by a trend line with positive slope. Demand must always be greater than or equal to zero. The seasonal component consists of “annually recurring movements above and below the trend line and are present when demand fluctuates in a repetitive pattern from year to year.” [ibid] For a seasonal component to be included in the model, it must be clear that the effect occurs during the same period from year to year, and should be able to be described as having a definite cause. For example, if the disposal of used motor oil occurs at a higher rate during the summer, and this has a noticeable effect during the same period each year, then the seasonal component should be included. The random component, frequently referred to as noise or residuals, accounts for the variations in the data that cannot be otherwise explained.

Mathematically determining these components is typically performed one component at a time, starting with the linear trend component. Expressing demand as a function of time is performed by determining the best fitting straight line through the data, for which the most common approach is the use of linear regression. This is often referred to as an Ordinary Least Squares Linear Model, since the slope of the line is determined by minimizing the sum of the squared distances of the data points from the line. The basic

equation for a straight line that describes this linear relationship of demand (Y) at time (t) is

$$Y_t = \alpha + \beta t + \varepsilon_t \quad (3.1)$$

where α is the intersection of the line with the vertical axis when $t = 0$, β is the slope of the line, and ε_t is the error between the observed value and the estimate. Both α and β are unknown, but can be estimated to minimize mean squared error. To determine if the trend line has captured the behavior of the data, we can calculate the coefficient of determination, r^2 ; a high coefficient of determination indicates that the trend describes a high percentage of the variance in demand. This coefficient is determined by computing the ratio of the explained variance over the total variance. A value of $r^2 = 1$ would indicate that the model explained all of the variance, but this is virtually impossible to achieve with real data. It is also helpful to plot the trend line along with the actual data values over time to “see” if the linear model is capturing the true trend of the data, or is being significantly affected by one or more values far from the other values, called outliers. Outliers can be identified by computing the Cook’s distance of the data values, which measures the influence that specific data points have on the regression coefficients. [Cook and Weisburg, 1982] Whether these outliers should be included in the analysis or not is a matter of judgment by the analyst.

Determining seasonal or time of year effect is much more challenging. The demand is first “detrended” by subtracting the linear trend line from the observed demand described by the data. By plotting this detrended data, the analyst may be able to determine if there is evidence suggesting a seasonal effect. As mentioned previously, it is desirable that any effect included should be able to be explained by some identifiable

cause, or a false impression of seasonal trends may cause the analyst to model an effect that is not truly present. One way to compute seasonal effect coefficients, when differences are noted or expected, is to calculate (a) average demand per period (week) over the entire historical data cycle (two years), and compare this to the (b) average demand over a specific time of year (the 3rd week of November each year). The ratio of these two averages ((b) divided by (a)) gives a seasonal index for that period during the forecast cycle; [Tersine]. A ratio greater than one suggests that the period in question is expected to have a demand higher than the average of all periods. High variance between periods close together in time, as well as a lack of observed values for a specific time period, may dilute the information obtained from this analysis.

The last component that is to be considered is the random component. The random component accounts for the variance remaining in the data when trend and seasonal components are removed, and we are left with only the residuals. When a model can account for a large percentage of the total variance through trend and seasonal components, the random component appears as small changes and has little effect on demand estimates. If, however, there is a large amount of variance that cannot be explained, the random component may have a sizable effect on the accuracy of forecasts. Additionally, sometimes a single point estimate for demand is not desired, but rather we desire to predict that the true demand would fall within a range of values that we specify, with some probability of confidence. This range of values grows larger when the random component accounts for a greater percentage of total variance. The distribution of the residuals can supply additional predictive power. It is often initially assumed that these residuals will be independently and normally distributed about the estimated values, which

allows for stating that with approximately 95% confidence the original point estimate will be within 2 standard deviations of the true value. When using actual data, the approximate validity of this convenient assumption should be checked.

It is important to note that one of the basic uses of time series analysis is to suggest how well the past might be a good indicator of the future. If serious disruptions in the process occur, accurate individual forecasts might not hold. In this thesis, we could consider the start or stop of a major research activity on site at LLNL to be a serious disruption that could affect the basic analysis. In this case, additions or deletion of experiments and or facilities generating demand would have to be analyzed separately from the base case depicted here, and added or subtracted from the resulting forecast. An example of this would be the building of the National Ignition Facility, which may have significant effect on the lab-wide generation rates for a number of waste streams.

2. The Amount of Time Waste is Stored

The other major indicator for future storage requirements is the amount of time that the wastes will spend in storage. The data that has been provided by LLNL deals with wastes handled under the “old” system only, when time was not a major concern for the personnel handling wastes in the WAA. Further, time to perform many functions that are now being shifted to the WAA was not included in these data. Primarily, the waste handling time data has been analyzed to determine the effect of a WAA technician processing waste under the “old” system. These times form a baseline case for the “new” system. To these time values, the time estimates for the additional functions of the WAA under the new system are then added. This analysis represents a worst case scenario,

since decreasing processing time is a primary concern during this re-engineering effort. A basic assumption is that the new process will only shorten the time for processing waste. Data analysis indicates that the additional time required to perform the extra functions under the new system, added to the time it takes to process waste under the old system, will frequently cause the time that a container is stored in the WAA to exceed the 90 day limit. If this were to occur, the wastes would have to be brought into an on-site TSDF permitted to accept that waste, or a letter written to the California Environmental Protection Agency (Cal/EPA) explaining why the waste could not be shipped off-site within the 90 day limit (and perhaps incurring a fine). Hence, it is important that the waste processing times for the new system be shortened.

When trying to anticipate the time to complete processing under a new system, for which no historical data exists, frequently the best (and possibly only) estimate is that which an expert familiar with the process in question makes. When data have become available through pilot testing of a process, this data is incorporated along with the expert opinion to form the basis for estimates whenever possible. For example, when faced with the change of the process for handling wastes, it is clear that the time required to process a waste element under the “old” system will not necessarily reflect the time that it will take to process wastes under the “new” system. When data are not available, the opinion of one or more experts familiar with the process has been sought, and excursions based on that estimate attempted. These estimates and excursions, applied to the simulation model described in the Chapter V, form the basis for estimating total storage capacity required and aid in determining the feasibility of closing storage facilities.

D. ANALYSIS BY ZONE

The techniques listed above are applied to model the quantities of waste storage demanded in each Zone's Consolidation WAA. The waste storage demand is the sum of storage demands placed on the individual facilities targeted for closure, and the facility now designated at the Consolidation WAA. The primary goal is to validate or disprove the concept of decreasing quantities of waste requiring a decreasing amount of storage space, as well as determining what that requirement would be. If the waste storage demand does not exhibit significant effects of seasonality or trend, then the empirical distribution for the weekly quantities of waste generated was computed. If no common distribution (i.e. - normal, gamma, etc.) was found that could well describe the weekly waste arrivals, as measured by a Kolmogorov-Smirnov goodness of fit test at 95% confidence, then the empirical distributions derived from the data set is used. The Kolmogorov-Smirnov test is used to determine if the sample data set could have come from the distribution it is compared against, using the greatest absolute vertical distance between the empirical distribution of the data and the distribution function value that would occur for the distribution the data is being compared against. A high p-value indicates a better chance that the data set values could have come from the distribution it is being compared against. For purposes of this thesis, a p-value greater than 0.05 will indicate that a distribution is acceptable for modeling arrivals. This distribution then describes the number of arrivals per week for wastes containers used in the simulation model for activity in that zone.

Note that the distributions used to model the discrete weekly arrival data are for continuous variables. The arrival portion of the simulation model generates a continuous

random variable, and then rounds it to the nearest integer value. Since no assumptions can be made about the greatest number of containers of a given type that could be brought into a facility in a given week, only distributions which are not constrained to the right (can attain any value greater than zero with some probability) are used to model the data. The one exception is, of course, that the empirical distribution is constrained by the highest value attained during the two years that were analyzed. Additionally, it will be assumed that the number of containers being disposed in a given week is independent of the number of containers disposed in the previous or following weeks (a certain number of containers arriving in one week will not necessarily imply a certain number of containers will arrive the next week).

Following this analysis, the distribution of the amount of time required to service the wastes under the “old” system has been approximated by fitting a standardized distribution to it. This provides a baseline case for the distribution of technician service time under the “old” system. This is a projected worst case technician service time, as well as being useful for trials on the waste handling simulation model. The technician service time is only part of the total service time for the “new” service process, but it is the only portion of the total time for which historical data are available. All other portions of the total service time must be estimated using the opinion of experts at LLNL; sensitivity analysis is performed later to determine the effect of errors in these estimates on the model results. Again, the distributions tested for use in modeling service times were distributions that are unconstrained to the right (can achieve unconstrained high values). While service is typically constrained to 90 days, there were occasions when items took much longer to service. While the available data records the service times as a number of days (discrete),

continuous distributions can be used to model the time. Standard distributions which best captured the shape of the data are used to model service times in the simulation model. The two primary distributions that are considered are the exponential (or shifted exponential) and the gamma (or shifted gamma). The distribution parameters were estimated using method of moments calculations (for the gamma) or examining the variance of the distribution (for the exponential). For the shifted exponential, the shift was estimated as the sample mean minus the sample standard deviation (always a positive value). For the shifted gamma, the shift was estimated as the lowest observed value.

The percentage of wastes that are incompatible for side-by-side storage was also computed for facilities in which physical separations of waste (cell walls) are not present. This percentage is needed to determine if storage compatibility will in any way limit the capacity of the Consolidation WAA. If there is a large quantity of items that are neutral with respect to storage compatibility (meaning compatible for storage with both items that cannot be stored side-by-side), then these neutral items can be assumed to be stored between incompatible items to act as a physical separation. It can further be assumed that wastes which are incompatible with many other wastes or otherwise present safety concerns when stored with various waste types, such as cyanic compounds and explosives, will be stored only in areas designated for receipt of these materials, and are therefore outside of the scope of this analysis.

The methods used for analysis will be described in detail for large containers disposed in Zone One, with the analysis for the remaining containers and Zones described in Appendix A : Graphical Analysis . Only the results for each remaining Zone's waste analysis will be given in this chapter.

1. Zone One Large Containers

Zone One is in a “Red” security area. This Zone has been designated as the Pilot Program Zone for implementation of the re-engineering plan, and is probably the most ambitious with regard to the amount of storage space being lost to facility closures. This Zone is also the location of the Area 612 TSDF, a recently remodeled and expanded facility that is the primary focus of the Consolidation WAA concept for Zone One. The traditional role of this facility has been to store a large percentage of various waste forms generated throughout the lab and prepare it for off-site transfer. Building 612-4, the hazardous waste storage facility measures nearly 100’ by 40’ and contains five waste storage cells, each with capacities for 32 to 40 pallets of material per cell. Each cell is separated from the adjacent cell(s) by a solid bulkhead, and is protected in the event of a spill or fire by an overhead sprinkler system. The facility is designed to meet the requirements of the Part B RCRA Permit, which allows the facility to store hazardous waste for up to one year. Under this permit, each of the five cells is designated as storage for specific groups of waste types, which is not required of a WAA.

Under the rigid requirements that must be met as part of this permit, all waste must be completely classified and placed in Department of Transportation (DOT) approved containers before it can enter the facility. As mentioned in the introduction, ensuring that wastes were properly classified, labeled, and containerized for shipment was the responsibility of the WAAs under the old system, and this responsibility is now being shifted to the generator. Once wastes enter the facility, a percentage of waste containers undergo a chemical analysis as a verification of the classification process. Those waste containers selected for chemical analysis are put on “hold” and cannot complete

processing until the results from analysis are returned to the storage facility. The waste then accumulates in the storage area until it can be shipped. It is anticipated that eventually this facility may be able to be reclassified as a WAA; the reclassification would require the wastes to be disposed of in 90 days or less. The current (interim) permit is being maintained until the pilot program verifies that the 90 day or less time limit can be met. Zone One is the only zone in which a TSDF is being considered for designation as a Consolidation WAA.

There are currently 7 WAAs in Zone One scheduled for consolidation to the 612-4 facility; 3 WAAs which are planned for maintaining open indefinitely, and one WAA (WAA 511) which is to be kept open during the pilot phase of the program. Once the pilot program has been satisfactorily completed, wastes from WAA 511 will also be directed to the 612-4 Consolidation WAA.

In the interim, waste that cannot be fully classified by the generator is being sent to WAA 511. Those wastes arriving at WAA 511 which can be completely classified, can have the classification validated on a random basis, and can be manifested to a shipment within the 90 day requirement will be shipped directly off-site from WAA 511. If wastes approach the 90 day limit without being able to be shipped, the 612-4 facility will still be able to accept the waste and store it for up to an additional one year (under the RCRA Part B permit), or until it can be shipped. This would require additional handling of the waste, and conflict with the goal of reducing reliance on permitted facilities, so it is generally avoided.

During the period of Jan. 1995 to Dec. 1996, there were over 1500 hazardous waste disposal requisitions processed in Zone One. Of these, 471 were of waste

containers smaller than 10 gallons in capacity, 1013 were of containers from 10 gallons to 85 gallons in capacity, and the remaining requisitions were for various sized boxes of solid wastes or large portable containers and trailers of from 110 to 5000 gallon capacity. The large volume boxes (up to 4' by 4' by 7') were primarily disposals of light bulbs or lab trash (non-RCRA wastes), which occurred too infrequently over the time span to accurately model, and will be handled separately from more traditional container disposals. The trailers are stored in either the Area 612 Portable Tank Storage Unit or the Area 612 Tank Trailer Storage Unit, depending on size, and are typically scheduled for disposal on an individual unit basis. They will not be considered in this analysis.

By applying the 5GCE approximation for the various containers, it was determined that on the average only approximately 12% of the storage space required by wastes being generated in the WAAs targeted for consolidation in Zone 1 was utilized by acidic wastes, having a pH of 6.5 or less, and only approximately 5% of the storage space was utilized by alkaline wastes, having a pH of 8.0 or higher, during the two year period for which data was analyzed. The physical separation of liquid wastes of incompatible pH is a primary concern, since an accident in which two dissimilar liquids come in contact can be explosive. Since only a small percentage of wastes are incompatible in this way, it is therefore assumed that the other items (83% of total storage needs) can be used to keep these materials physically separated without negatively affecting total storage capacity.

The next step is to determine the trend for waste arriving at the storage facility from the designated WAAs in Zone One. The weekly arrival process was therefore plotted against the calendar weeks that the wastes arrived, and the S-Plus linear model function was used to perform OLS linear regression. Examining the output of the OLS

linear regression showed a slope of -0.0017 , over 104 weeks. It was therefore determined that a significant decrease in the storage needs for large containers in Zone One has not been achieved over the last two years. In fact, the trend for weekly disposals of these large containers has remained essentially constant at 9.730769, or just under 10 large containers, or 2.5 pallets, per week, with a standard deviation (describing the scatter of data values above and below the trend line) of 1.3094; (see Figure 3.1). As a side note, the residuals are frequently assumed to be normally distributed about the trend line, but this assumption may be less valid when the data values are bounded by zero, as seen here.

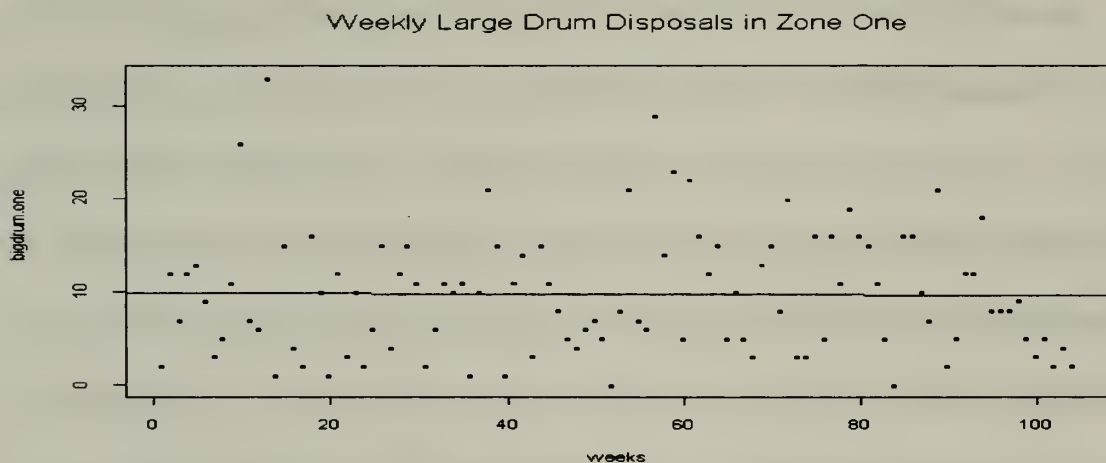


Figure 3.1

The trend line alone only accounts for a small portion of the variance in the data, denoted by a multiple R-squared value (which denotes the correlation of data values to time) of < 0.10 . This indicates that the variance that is seen week to week did not change significantly in response to time moving forward. In other words, with very little change

in the number of containers arriving over time that can be attributed to a trend, it is more difficult to predict exactly how much waste will come in the following period.

The next step was to determine if the data exhibits any seasonal trending. By observing the random pattern of data points distributed above and below the trend line, there is no clear indication of seasonal influence in this data set. In fact, it appears that there is little difference at all in the average number of containers being disposed from one season to the next. Performing analysis of variance (ANOVA) hypothesis testing, with the null hypothesis being that the mean number of containers disposed each week over 8 disjoint periods of time (calendar year quarters) has remained constant, reveals that there is insufficient evidence to indicate otherwise, with a p-value of 0.19405. This can be seen graphically by observing a graph of “running” box plots. Figure 3.2 depicts the box plots of the weekly number of large containers that would have gone to the Consolidation WAA over the 8 disjoint time periods depicting calendar year quarters. The center line of the box plot indicates the mean number of arrivals for the given quarter.

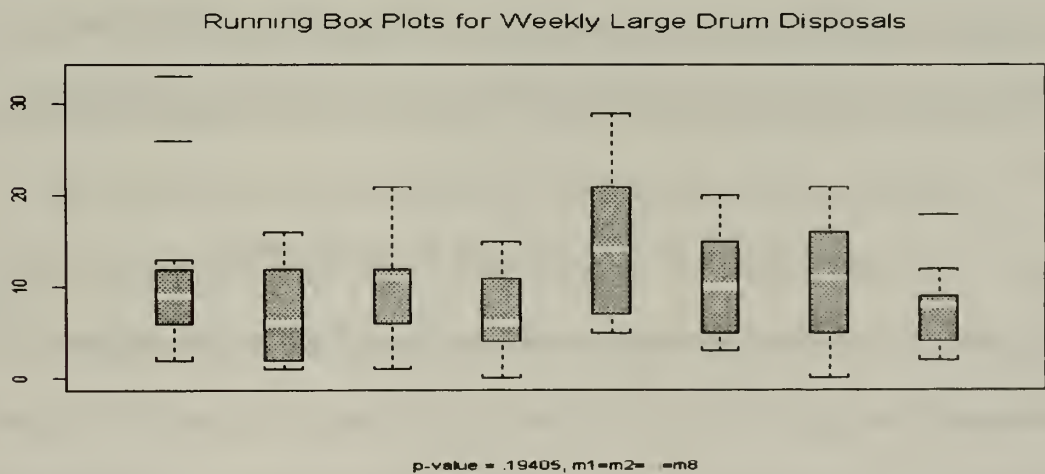


Figure 3.2

The number of large containers being disposed is noted to have a mean of 9.73 containers, and this average number can be used in the expected value (Little's Formula) model, but additional information regarding the distribution of the number of containers being disposed each week will be needed for use in the simulation model. To determine which distribution adequately summarizes the historical data, several common distributions are compared to the data values and the best approximation is used. If standard curve fitting techniques fail to determine a suitable distribution to use as the model, an empirical distribution of the number of large containers arriving per week can be used. For large containers in zone one, however, a "discretized" Gamma distribution is used to describe the number of containers arriving. The parameters for a continuous Gamma distribution were estimated from the data using Method of Moments [Mendenhall, Scheaffer, Wackerly, p. 367] calculations. The calculations for the estimated parameters of the distribution were performed using an S-plus function written by Prof. S. Buttrey at the Naval Postgraduate School for ease of repeated use. The gamma density function is recorded in literature using various functional forms. In our discussion, the functional form is

$$f_Y(y) = e^{-(y/\beta)} y^{(\alpha-1)} [1 / (\Gamma(\alpha)\beta^\alpha)] \quad (3.2)$$

Using the above form, the distribution has mean = $\alpha\beta$ and the distribution's variance = $\alpha\beta^2$.

S-Plus requires that the data be "scaled" by dividing all data values by the scale parameter, and then performing goodness of fit on the scaled data by comparing these scaled values to those obtained from a theoretical standardized gamma distribution with

the estimated shape parameter. Calculated p-values reflect goodness of fit on this standardized gamma distribution. [Olkin, Gleser, Derman, 1994] (see Figure 3.3).

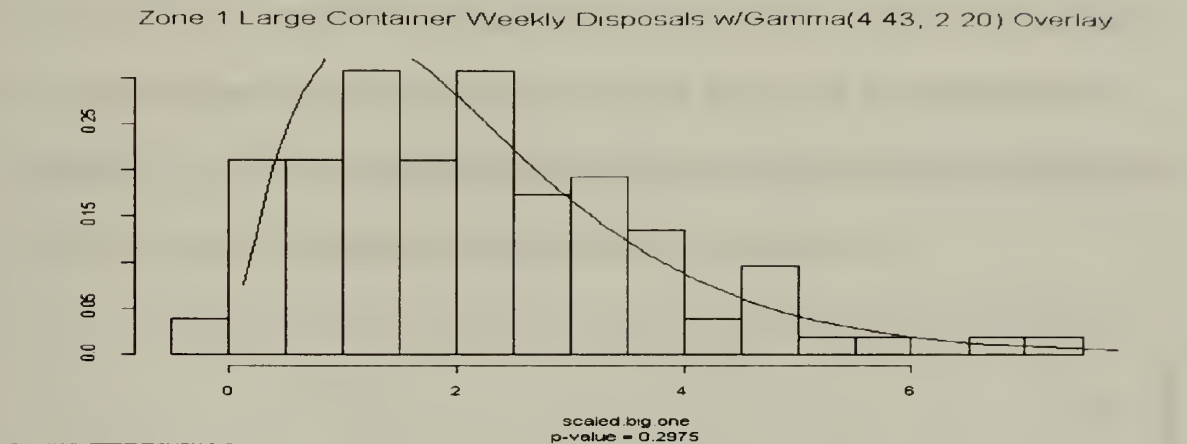


Figure 3.3

The values on the X-axis of Figure 3.3 are the number of containers disposed during a week divided by 4.429 (the scale estimator), resulting in a standardized gamma with estimated shape parameter 2.20. The original data values ranged from 0 to 32. The Kolmogorov-Smirnov (KS) goodness of fit test was then used to determine how well the resulting standardized gamma distribution fit the scaled data, and the result was a p-value of 0.2975. Note that the goodness of fit test is fitting a continuous function to data which can only attain integer values. Data values cannot, however, ever be truly continuous.

The simulation model will generate a random number from an unscaled (2 parameter) gamma distribution, and truncate the value to the next lower integer. Since we desire the value of the closest integer, 0.5 will be added to the random number prior to truncation. The resulting integer value will model the number of large containers arriving for that week. An example for this process is provided in the introduction to Appendix A.

The amount of waste being generated is, of course, just one of the factors which determines how much storage space is needed. We must also look at how long each item of waste stays in the facility undergoing service. This is described next.

The histogram for the amount of time that large waste containers spent in the WAA (in days) for processing is provided below (see Figure 3.4).

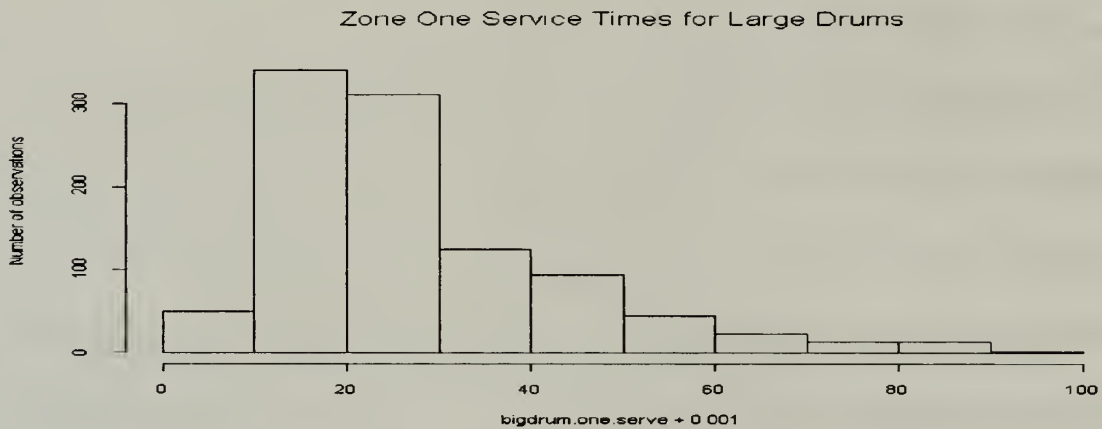


Figure 3.4

In zone one, there were very few containers that were of state or federally regulated waste, so the entire group of large containers was modeled as having a single service time distribution. In general, state and federally regulated waste service times were found to be different from other hazardous waste service times within a given zone and were modeled separately.

The histogram above shows that only a small percentage of large waste containers have taken less than two weeks to be processed, with a majority taking from fifteen to thirty days. In fact, under 5% of the containers took less than 10 days to process. The question is then to determine which common distribution could best describe these data. One such assumption often made in queueing theory is that service time is an exponentially distributed random variable. Examining the data for large container service times, it was

observed that the mean was just over 26 days and the standard deviation was 16.1 days. These values are well represented by a shifted exponential distribution of $10 + \text{Exp.}(16.1)$. This means that for each arrival, an exponential random variable will be generated for the service time, with a mean value = 16.1 days, and then 10 days will be added to that value. This resulting sum will then be assigned as the amount of time required for a technician to complete traditional WAA service on the container. (see Figure 3.5).

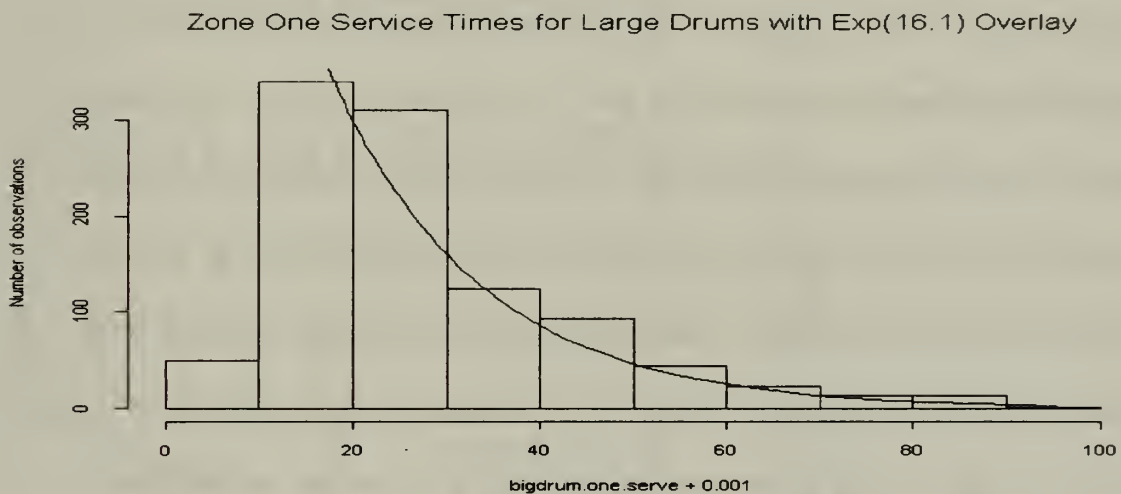


Figure 3.5.

The fit of the data was tested by removing the service times less than 10 days, and subtracting 10 days from all the other service times. This transformed data set was then compared to an exponential distribution with a mean of 16.1 days, using the KS goodness of fit test in S-Plus, which resulted in a p-value < 0.01 . With over 1000 data points, however, it must be recognized that goodness of fit tests will often fail. The right tail of the exponential distribution may also be too long, since extremely high data values were rare. Goodness of fit tests often fail to capture probabilities far out on the tail. It was, however, the best fit of all distributions attempted. The above graph demonstrates that the distributional form of the data appears to be captured well by the chosen distribution;

Appendix A shows the greater detail of the analysis performed, as well as the results of QQ Plots. A QQ Plot demonstrates the comparison of a hypothetical distribution's value at various quantiles to the quantiles of the empirical distribution of the historical data.

This distribution of service times cannot account for efforts taken to ensure that wastes are processed in under 90 days, and in analyzing the data it was noticed that there is often an increase (a "bump" on the histogram) in the number of items completing service just prior to this 90 day limit. For Zone One large waste containers, the distribution described by this exponential gives us a probability of only 0.00695 that an observed value will be greater than 90 days, and items that the simulation assigns these long service times to should be rare occurrences, having negligible effect on the model's total amount of waste in storage. When the hypothetical distributions are used in the simulation model demonstrated in Chapter V, the simulation will not attempt to alter the values for the age of waste greater than 90 days. As a side note, the historical data set of 1013 entries also included one value greater than 90 days, resulting in an empirical probability of 0.0009872 for such an occurrence. It must be reiterated, however, that distributions fit to data frequently do not capture the shape of the data in the tail of the distribution.

The results of data analysis for all other wastes is denoted in the following table (see Table 3-1). The analysis for the remaining wastes is included in Appendix A. The only zone which showed a significant decrease in the number of containers being sent to storage facilities was small containers being generated in Zone 4. Other zones showed no appreciable decreases in weekly quantities of containers sent to the WAAs over the two year period analyzed.

Zone	Container Size	Number of Observations	Avg. Number of Containers per week	Variance of Containers per week	Distribution (Discrete)	Resulting P-value for KS Goodness of Fit	Avg. Service Time	Variance	Distribution	Resulting P-value for KS Goodness of Fit
1	Small	458	4.53	27.94	Empirical	N/A	32.1 Days	354.75	13 + Exp(19)	< 0.01
1	Large	1013	9.73	43.52	Gamma(2.197, 4.429)	0.2975	26.6 Days	257.91	10 + Exp(16)	< 0.01
2	Small (H)	(749) 878	(0.85) 6.87	19.28	Gamma(2.48, 2.77)	0.3175	28.8	247.27	7 + Gamma(1.9, 11.3)	< 0.01
2	Small (S)	(70) 878	(0.08) 6.87	19.28	Gamma(2.48, 2.77)	0.3175	26.62	244.1	13 + Gamma(1.69, 6.41)	0.1011
2	Small (F)	(50) 878	(0.07) 6.87	19.28	Gamma(2.48, 2.77)	0.3175	36.27	563.27	10 + Gamma(1.25, 21.08)	0.5815
2	Large (H)	(39) 54	(0.72) 0.52	0.52	Empirical	N/A	40.41	665.35	13 + Gamma(1.16, 23.65)	0.1645
2	Large (S)	(15) 54	(0.28) 0.52	0.52	Empirical	N/A	54.8	842.46	13 + Gamma(2.22, 18.81)	0.3122
3	Small	403	4.03	17.48	Gamma(0.937, 4.298)	0.0823	34.43	383.49	15 + Exp(19.6)	< 0.01
3	Large(H)	(138) 167	(0.83) 1.65	3.85	Empirical	N/A	41.32	585.97	Gamma(2.93, 14.08)	< 0.01
3	Large(S)	(29) 167	(0.17) 1.65	3.85	Empirical	N/A	47.63	691.55	Gamma(3.39, 14.03)	0.5301
4	Small(H)	(1671) 1920	(0.87) 18.69	85.56	Normal (18.46, 9.25)	0.5	28.27	280.72	12 + Exp(16.75)	< 0.01
4	Small(S)	(55) 1920	(0.03) 18.69	85.56	Normal (18.46, 9.25)	0.5	32.8	369.73	Gamma(2.96, 11.07)	0.5278
4	Small(F)	(193) 1920	(0.10) 18.69	85.56	Normal (18.46, 9.25)	0.5	40.1	475.47	8 + Gamma(2.18, 14.73)	0.0146
4	Large(H)	(880) 1170	(0.75) 11.26	28.41	Normal (11.26, 5.33)	0.5	33.62	383.3	9 + Gamma(1.65, 15.11)	< 0.01
4	Large(S)	(125) 1170	(0.11) 11.26	28.41	Normal (11.26, 5.33)	0.5	27.66	180.52	Gamma(4.27, 6.47)	0.0368
4	Large(F)	(165) 1170	(0.14) 11.26	28.41	Normal (11.26, 5.33)	0.5	33.83	466.05	Gamma(2.47, 13.69)	0.0002

NOTES:

(H) : indicates hazardous only waste class.

(F) : indicates Federally regulated waste class.

(S) : indicates State regulated waste class.

(number 1) number 2 : indicates number of observations of that waste class; a portion of total container arrivals or arrival rate of given container size recorded for that zone.

Distribution for arrivals (waste containers per week) result in discrete numbers of containers when used in the simulation.

Distribution parameters are listed as Gamma (shape, scale), Normal (mean, s.d.) and Exponential (mean).

Table 3-1.

IV MATHEMATICAL MODELS FOR STORAGE

A. THE USE OF MATHEMATICAL MODELS

Mathematical models are a very useful in performing system analysis, and can often provide an enhanced understanding of system performance. When developing a model for a physical system, there are often standard mathematical models or modeling approaches that have been shown in the past to be useful for classes of systems. For the storage problem at hand, one such class of models arises in queueing theory.

Queueing theory is best described as the study of “a class of models in which customers arrive in some random manner at a service facility. Upon arrival, they are made to wait in queue until it is their turn to be served. Once served, they are generally assumed to leave the system.” [Ross, pg. 351] Utilizing various modeling assumptions, queueing theory presents methods for determining the average number of customers in the system as well as the average amount of time a customer spends in the system. If we consider the customer to be a container of waste, then the parallels of this class of models to the problem presented in this thesis should be evident.

B. FORMULATING THE MATHEMATICAL MODEL

The application of queueing theory requires information regarding the arrival process to the queue, service times within the queue, and the number of resources (servers) allocated to process the customers.

Arrivals to the system may increase during some periods of time, such as during certain times of the year. Such increasing and decreasing arrival rates are characteristic of a non-homogeneous arrival process. If time does not appear to have significant effect on arrival rates, then the process is called homogeneous. As indicated in the Chapter III and Appendix A, arrival of waste containers for disposal can be considered to be a homogeneous arrival process.

Waste container arrivals are recorded as a number of containers arriving on a specific date. The number of containers that arrive has been discovered to vary widely from one time period to the next, but with no time of year effect. As a simplifying assumption, the model that will be developed for this thesis will consider wastes arriving during a week as a batch at the beginning of each week. The numbers of various sized containers arriving each week will be modeled as independent, identically distributed random variables, each coming from a distribution derived from the data analysis of the waste arrival process discussed in the last Chapter III. The average rate of arrivals of waste in container size (i) is the average number of containers of type (i) arriving each week. We can call this average arrival rate λ_i , for which we derived an estimate in the previous chapter.

This waste then undergoes service before it is ready to be shipped. The amount of manpower available to service the waste is considered to be unlimited, since any backlog for service would be compensated for by a reallocation of resources. Each container of waste of an arriving batch will therefore begin service immediately. The amount of time that each waste container spends undergoing service is then modeled as a realization of an independent, identically distributed random variable described by a distribution. Wastes

often undergo sequential service tasks. Each task must be completed before service is completed. The total service time is expressed as the sum of the times that it takes to complete all the tasks in the sequential service process. If interested in only the average amount of time it takes for the waste to complete service, we can view this average as the sum of the average times to complete each of the tasks involved. This average time for a container of type (i) to complete service will be denoted as W_i . Shipments only contain items that have completed all phases of processing, and shipments must be scheduled in advance. In general, shipments depart on a set schedule, which we will denote by D time units between shipments. On the average, the amount of time that a container spends waiting to be shipped after completing service is $D/2$.

Since we are dealing with a system that has only one way to enter service (entering the WAA) and one way to leave (removal from the WAA), we can classify our system as an “open system.” The long run average rate at which containers will complete processing must therefore be equal to the long run average rate at which they enter processing [Ross, pg. 373]. An exception to this would be wastes accumulated in the WAA (for wastes approved for accumulation), meaning that a number of small containers are gathered into one container. The percentage of items affected in this way is small, and the accumulation process can be considered as a slight loss in the system, having negligible effect on storage demand.

The so-called Little’s Formula [Ross, pg. 353] enables us to compute the long-run average number of items in the system having knowledge only of the average arrival rate and the average amount of time that customers spend in the system. If we consider the long run average number of containers of type (i) in storage as S_i , then we have

$$S_i = \lambda_i (W_i + D/2) \quad (4.1)$$

Using the fact that we are dealing with an open system, the long run average rate at which containers complete service is λ_i , and the long run average number of containers that will be on an outgoing shipment is $\lambda_i D$.

Additionally, if we want to consider the average quantity of storage space being utilized, we may let

λ_1 = average rate of arrival for small containers (each requires 1 5GCE unit of storage space)

λ_2 = average rate of arrival for large containers (each requires 3 5GCE units of storage space)

W_1 = average service time for small containers

W_2 = average service time for large containers

D = time between shipments of all containers that have completed service

S = 5GCEs of storage space utilized

Therefore, the long run average amount of storage space utilized is

$$S = \lambda_1 (W_1 + D/2) + 3\lambda_2 (W_2 + D/2). \quad (4.2)$$

Similarly, the average age of each container type (i) when it is shipped = $W_i + D/2$.

Let us call the average age of all containers A. Then

$$A = ((\lambda_1 / (\lambda_1 + \lambda_2)) * (W_1 + D/2)) + ((\lambda_2 / (\lambda_1 + \lambda_2)) * (W_2 + D/2)) \quad (4.3)$$

While the average age and average number of containers in the system is useful information, information regarding how many items are leaving the system with ages approaching the 90 day limit and the percentage of time when storage capacity is not able to meet demand are the true deciding factors in the analysis of the re-engineering considered for this thesis. This type of information is not easily extracted from a queueing model without making additional simplifying assumptions, but can be obtained through simulation. This will be the focus of the next chapter. The averages obtained through applying the queueing model described above can, however, be used to verify that the simulation model is performing properly when dealing with the long run average.

A mathematical model with more detailed results can be found as Appendix E.

C. RESULTS OF MATHEMATICAL MODELING

A summary of the results of applying the mathematical model using input data obtained from Chapter III and Appendix A is provided in the following table (Table 4-1). Appendix B includes more detailed spreadsheets denoting how this summary was derived, as well as a definition of each of the systems considered. The primary focus of Table 4-1 resides in the effect on storage requirements resulting from various percentages of waste which are able to be pre-classified through use of the Waste Evaluation Form (WEF) prior to entering the WAA.

Figures 4-1 and 4-2 graphically demonstrate the result of the mathematical model applied under the varying assumptions of amounts of waste pre-classified.

	Zone	"Old" System	0% WEF	25% WEF	50% WEF	75% WEF
Avg. 5 GCE Weekly Storage Demand	1	148.56	180.59	140.92	108	75.01
Avg. 5 GCE Weekly Storage Demand	2	42.73	48.97	39.95	32.33	24.7
Avg. 5 GCE Weekly Storage Demand	3	54.29	61.81	49.16	38.25	27.13
Avg. 5 GCE Weekly Storage Demand	4	264.46	301.25	246.1	199.26	152.42
	TOTAL	510.04	592.62	476.13	377.84	279.26

	Zone	"Old" System	0% WEF	25% WEF	50% WEF	75% WEF
Avg. Age of Waste Departing WAA	1	31.85	38.5	30.01	22.92	15.84
Avg. Age of Waste Departing WAA	2	33.72	39.04	31.66	25.46	19.26
Avg. Age of Waste Departing WAA	3	40.24	46.48	36.55	27.95	19.35
Avg. Age of Waste Departing WAA	4	34.37	39.55	32.19	25.98	19.77

TABLE 4-1

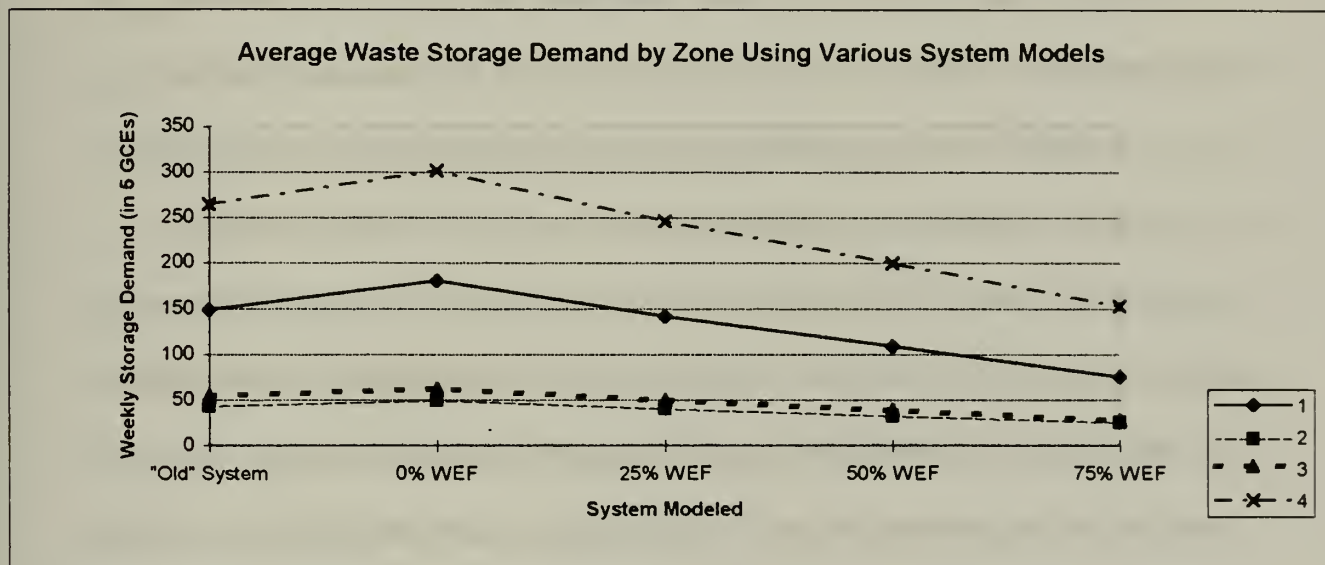


FIGURE 4-1

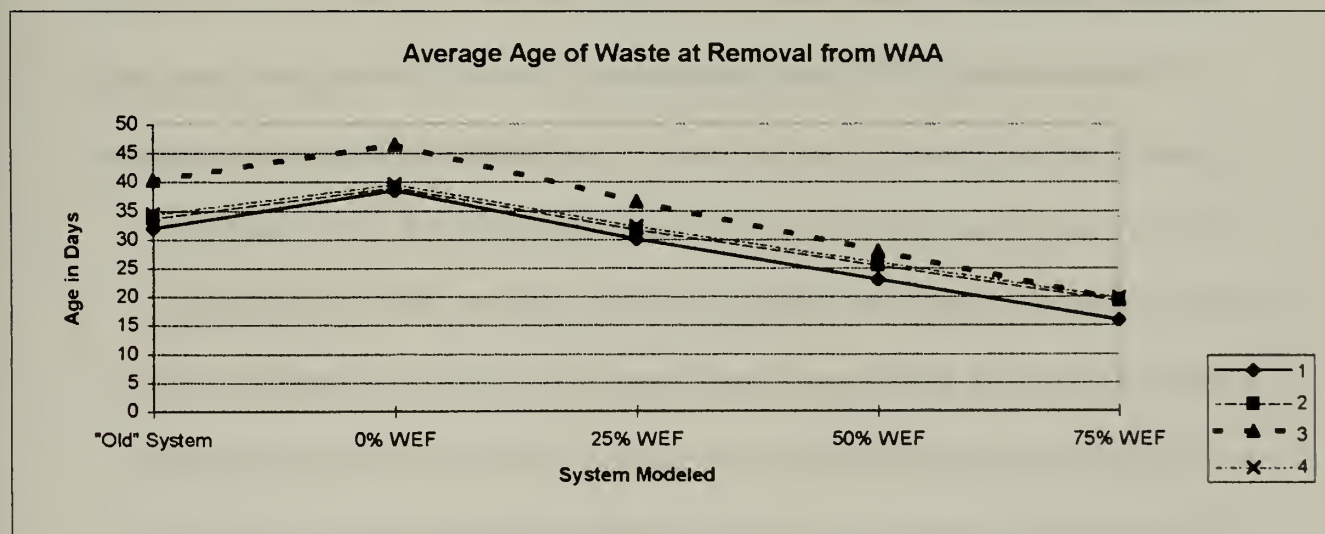


FIGURE 4-2

It is evident that introducing the re-engineered process of preparing items for shipment directly from the WAA actually increases the need for storage space if service times for the waste are not reduced through the use of the WEF. Adding the amount of service time required to perform the additional tasks that will be performed in WAA results in the average demand for storage space increasing by nearly 14%. This result should not be surprising.

It is also evident that by achieving a goal of categorizing 25% of all traditional hazardous wastes by WEF prior to entry into the WAA, the average total service time is decreased to slightly below that of the “old” system. This results in the average demand for storage space being lower than that of the “old” system. A “WEFable” amount of waste slightly less than 25% of total hazardous wastes will, on the average, place no additional demand for storage space on the system. This is essentially the break point for comparing average future demand for space to average past demand for space. This percentage does not, however, improve on the old system and would therefore not justify a change in the system.

Any percentage of “WEFable” waste beyond 25% yields the benefit of subsequent decreases in average demand for storage space. Since the current estimate of waste which is able to be categorized by WEF is approximately 50% [Fischer, R.], it is clear that a decrease in average demand for storage space can be achieved. While the percentage decrease in demand for storage space varies among zones (since some zones must reserve more space for state and federally regulated wastes), LLNL can expect approximately a 25% lower average demand for storage space among the facilities listed for consolidation if 50% of the waste can be pre-classified.

Additional increases in the percentage of waste able to be identified early in the waste generation process and also classified by WEF further reduces the average demand for space. The expected result of achieving a “WEFable” hazardous waste percentage of 75% is also shown. While it may be possible to increase this percentage beyond 75%, it can be seen that the average demand for storage space is decreasing at a linear rate as “WEFable” percentages increase. The costs of reaching higher percentages, however, may be non-linear. Data regarding these costs were not available, but it is generally assumed that, at some point, changes in a system will achieve a point of diminishing returns on investment. Determining this point is beyond the scope of this thesis.

The mathematical model allows for determining some quantitative results of implementing the re-engineering process, as well as demonstrating the benefits of pre-classifying wastes entering the WAA. By reducing the average demand, some reduction in infrastructure may be feasible to perform. The present mathematical model does not demonstrate the effects that the variability in weekly quantities arriving for disposal and variance in service times have on peak demand. It is peak demand that dictates the necessary quantity of storage space that must be made available. This will be explored in the next chapter through simulation.

V. SIMULATION OF WASTE STORAGE PROCESS

A. THE USE OF A SIMULATION MODEL

Simulation is the use of a model (frequently implemented on a computer), developed to approximate the behavior of a real world system, to conduct experiments and gain an understanding of the behavior of the system. The simulation model allows for the testing of various strategies without modifying the real world system, to determine the effect that changes could have. By analyzing the effects that changes have on the model, the decision maker can gain a better understanding of the changes that could occur in the actual system, allowing the decision maker to obtain an estimate of the impact a change may have without having to modify the actual system.

While perfection in a model can be a worthy goal, it is seldom possible to achieve. An approximation to the essentials of the “real-world” system is often adequate for decision making purposes. A “model” is a simplification, by definition. A computerized representation of an appropriate model can then be run many times, with variations of the model’s inputs, so as to gain insight into the sensitivity of the system to changes. Simulation of a system can sometimes be performed with pencil and paper, but the current availability of relatively low cost, powerful computers and the development of commercially available simulation software has facilitated development of useful simulation models which can adequately mimic real world behavior. By using computerized simulation tools “the model can be allowed to become quite complex, if needed to represent the system faithfully, and you can still do a simulation analysis. Other methods may require stronger simplifying assumptions about the system to enable an

analysis, which might bring the validity of the model into question.” [Kelton, Sadowski, Sadowski, 1996]. Simplifying assumptions are always required when developing a computerized simulation. Simplifying assumptions are critical to developing a model that can be understood and analyzed. As mentioned previously, simulating a real world system “exactly” is never possible, and the resources that would be required to do so would be astronomical. Rather, a simplified model that captures the essence of the problem to be studied, without becoming overly complex, is desired. Adequate data describing the performance of a system to be modeled is often not available, or the model represents a system that does not yet exist, so use of plausible assumptions and the opinions on system performance from knowledgeable experts is essential.

B. CONSTRUCTING THE WASTE STORAGE SIMULATION MODEL

The waste storage simulation model has been constructed utilizing the Student Version of *Arena*, a commercially available simulation software package developed and marketed by Systems Modeling Corporation. The goal has been to develop a model that allows for use of data on the number of items in storage and the amount of time that waste required to complete the process. As mentioned previously, the number of items in storage at any given time is governed by the numbers of various sizes of containers of waste arriving each week to the facility and the amount of time that each container spends in the facility. The average number of items in storage is approximated using the mathematical models developed in the previous chapter, but the distribution of items in storage is much more difficult to derive mathematically. This distribution, and the probability that certain storage capacity limits are exceeded, can be approximated by

analyzing the output of a simulation. The long-run average number of containers in storage found by using the mathematical model is also useful to verify that the simulation is behaving properly and generating values close to what is expected.

Data analysis performed in Chapter III and Appendix A allowed for modeling the random number of waste containers arriving during each week, as well as the duration of the time that the wastes spent in the system under the “old” process. Since interarrival times are not available for waste coming into the facility, waste arrivals are modeled as a batch of items, the number of items conforming to the empirical or standard distributions obtained in Chapter III and Appendix A, arriving at discrete points in time, specifically every Monday morning. It is also important to note that the Student Version of *Arena* may quit prior to completion if over 100 containers are in the system at the same time, and therefore the number of containers arriving during a week may sometimes need to be transformed. For example, in Zone 4 we can expect a long run average number of small containers in storage of 88.35 containers. Since the simulation model will allow for the number of containers to arrive to be random, it becomes evident that the 100 container constraint of the software will very likely be exceeded during prolonged simulation runs. Therefore, the arrival process may need to be modeled by having each entity in the simulation represent 2 or more containers to stay below the program constraint. It will be expressly noted when circumstances required using a transformed arrival distribution, since a linear transformation of arrival quantities may not have a direct linear affect on the distribution of storage required. The full commercial version of *Arena* does not include this constraint. The full commercial version, however, was not available for use (since it is quite expensive) and the student version met most needs. Naval Postgraduate School

System's Management Department maintains a commercial license for this product, but it is limited for use in training and evaluation only.

The amount of time that classification and containerization of wastes (the traditional role of the WAA under the "old" system) will require is based upon the results of Chapter III and Appendix A data analysis for the basic scenario. This amount of time is viewed as the worst case for the re-engineered system. Further reductions in this time, based on the opinion of experts regarding what the re-engineering is expected to accomplish was examined. While it is true that wastes that are rapidly approaching the 90 day limit would be dedicated extra resources to ensure that they are removed from storage before time elapses, it is assumed that this will be a small percentage of the total wastes handled. The effect of a randomly modeled service time exceeding 90 days will have little effect on the model as a whole since the probability of multiple occurrences is low.

A central concern of the re-engineering is in having material classified prior to arrival at the WAA, which is accomplished by having the material data recorded and reviewed by a chemist. This is performed by completing a Waste Evaluation Form (WEF) on the waste. Waste which arrives at the WAA packed in a DOT approved shipping container, and properly recorded on a WEF, do not require traditional WAA technician service.

The amount of time that wastes spend undergoing chemical analysis is based on the assumption that 10% of wastes will be chosen at random for testing, and that this testing takes an average of 2 weeks to perform. Specific containers of waste selected for analysis are put on "hold" and cannot complete processing until the results of the analysis are returned to the storage facility. While only a point estimate was readily agreed upon,

it was noted that this time did vary, and generally did not take more than 3 weeks or less than 1, and was most likely to take about 2 weeks [Gagner]. Based on this, it was assumed that a normal distribution having a mean of 14 days and a standard deviation of 3 days could capture the essence of these variations.

Speaking with personnel in the LLNL HWM Shipping Department during experience tour, it was discussed that the amount of time that it takes to get a fully processed waste container scheduled for an outgoing shipment is typically one week. Thus, the model for this is a one week delay in processing before the item could be shipped. With respect to the actual system, it was further noted that wastes can be manifested for shipment within a day, with a special pick up occurring the following day, but this is normally reserved for items that need to be removed from storage immediately and could incur significant additional costs. Situations such as this were not modeled.

Wastes that have completed all necessary processing will be removed from the system as a batch at discrete points in time, with the basic scenario having this occur twice a week, on Tuesday afternoon and Friday morning. This will simulate twice weekly shipments to an off-site disposal facility. The frequency of the off-site shipments will be varied to determine its effect on storage space and age of materials at disposal time.

The processing of waste containers is assumed to occur with all containers undergoing processing at the same time. This assumption allows for the service process to be modeled as an infinite server queue. This implies that containers of waste never have to wait for processing because all of the technicians are busy. While a technician does not physically process all wastes at the same time, and there are not an infinite number of technicians available to process the waste, this assumption allows for realizing some

general truths about the process itself. Specifically, if the storage facility has a great quantity of waste requiring service and processing time is being adversely affected, additional assets could be assigned to assist in the processing. While further analysis could determine the effect on processing time of overloading a facility's technicians, it will be assumed that ample resources will be provided to ensure timely processing of the wastes occurs. Manpower will not be assumed to be a limiting factor.

The simulated process can therefore be viewed as follows:

1. Waste containers arrive as a batch each Monday morning, and are placed in the storage facility.
2. Wastes undergo processing which consists of three parts:
 - Technician handling (may be different for various waste classes)
 - Random Chemical Analysis (10% of items)
 - Manifesting to a shipment
3. Once Manifested, wastes wait until the next truck arrives to pick up the waste, and are then removed from storage and shipped off-site.

Once the "old" system has been modeled to determine the amount of storage capacity required if the "old" system was maintained, the estimates for the time to process waste under re-engineering are applied. These estimates must be based on expert opinion. For example, Mr. Robert Fischer, the LLNL Waste Generator Services Group Leader, reported that there was insufficient data to give exact information on service times in the areas which had already completed some consolidation activities, but it was estimated that 50% of the waste was now being classified by WEF and containerized (in DOT approved

receptacles) at the generation site, requiring no traditional WAA service on these wastes. Additionally, it was reported that as of July, there were no containers that were requiring over 90 days to complete the entire service cycle, from arrival at a WAA (or Consolidation WAA) to off-site shipment. [Fischer, prior communication]

The service time distributions being used in each simulation model are based on the traditional service times shown in Table 3-1.

C. SIMULATING THE OLD SYSTEM

1. Description of the Model

Under the “Old” system, the data analysis results from Chapter III will be directly applied to the simulation model. Additionally, it will be assumed that wastes will be shipped from the WAA once per week, as was typical of the weekly Waste Runs performed to transport fully classified wastes to TSDFs on-site.

A graph of this model constructed in Arena is shown below; Figure 5-1.

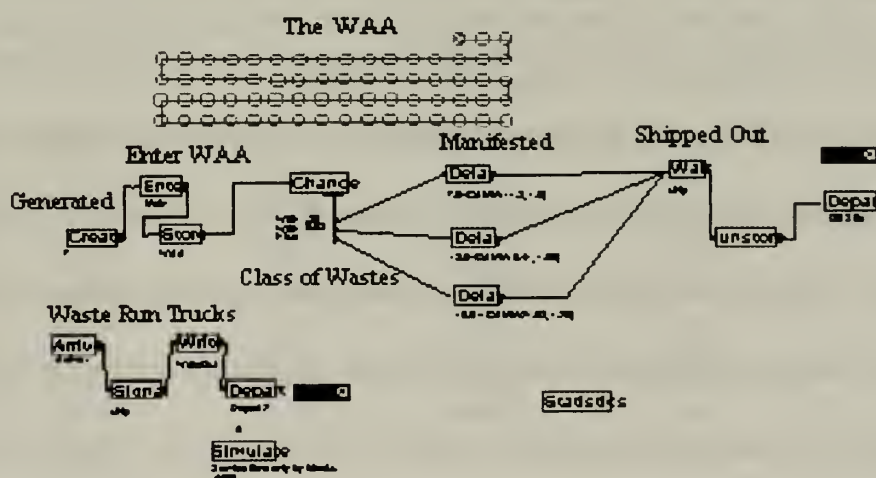


Figure 5-1.

The model can be read as a flowchart from left to right. A random number of containers of waste are “Created” each week according to the distribution obtained through analysis. Once created, each container continues through the rest of the model independent of other containers. Each waste container then “Enters” the WAA and is immediately “Stored.” It is then determined which class of waste each container belongs to; whether the waste is state or federally regulated or traditional hazardous waste is decided by a “Chance” that the waste belongs to one of the classes. A “Chance” block draws a uniform (0,1) random number and compares this with the cumulative probabilities of the various choices defined by the block. For our purposes, these choices were the calculated probabilities that a waste was either state or federally regulated wastes, or neither. The probabilities used are from analysis performed in Chapter III. When a zone was not noted as having wastes of a given class, this probability is zero. The containers are then “Delayed” in storage while service time elapses, with each having an independent delay time. Once the service time is complete, the wastes then “Wait” for a waste run truck to be sent. Waste trucks “Signal” their “Arrival” once per week, and then “Write” the amount of waste that is stored in the WAA to a file for future analysis. When a truck signals its arrival, all waste that is ready for shipment is “Unstored” and “Departs” the system (it is assumed that the truck can hold all wastes ready for shipment). The truck also “Departs” at that time. Specific “Statistics” are gathered by the program, including average age of waste at departure and average number of containers stored in the WAA for comparison with mathematical modeling results. The length of a run and the number of runs to perform is controlled by input to the “Simulate” module.

An example of the results will be provided here, with the remaining analysis left to Appendix C. Following the example, tables summarizing the results of analysis will be provided (Tables 5-6, 5-7).

2. An Example of Simulation Results, Zone 1.

A. Zone 1, Large Wastes, "Old" System.

Results for 10 Runs, each 1500 time units (days) in length.

Data gathered over last 1000 time units.

Zone 1 Large Container Simulation Results TALLY VARIABLES (Simulated Age of Waste at Disposal)				
Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	29.739	15.500	141.50	1346
Off Site_Ta	29.395	15.500	127.50	1472
Off Site_Ta	29.322	15.500	134.50	1303
Off Site_Ta	29.677	15.500	169.50	1420
Off Site_Ta	29.901	15.500	141.50	1324
Off Site_Ta	29.282	15.500	162.50	1383
Off Site_Ta	29.337	15.500	141.50	1463
Off Site_Ta	29.881	15.500	141.50	1248
Off Site_Ta	30.086	15.500	148.50	1314
Off Site_Ta	29.101	15.500	134.50	1475
Mean	29.57			
Standard Dev.	$0.33 / \sqrt{10} = 0.10$			
Expected Value	30.10			
DISCRETE-CHANGE VARIABLES (Simulated Number of Containers in Storage)				
Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	39.977	12.000	77.000	26.000
NSTO(WAA)	43.220	22.000	91.000	30.000
NSTO(WAA)	37.886	15.000	68.000	37.000
NSTO(WAA)	41.801	20.000	81.000	30.000
NSTO(WAA)	40.154	13.000	90.000	83.000
NSTO(WAA)	41.092	16.000	94.000	60.000
NSTO(WAA)	42.644	16.000	93.000	27.000
NSTO(WAA)	37.421	17.000	74.000	60.000
NSTO(WAA)	39.438	16.000	72.000	27.000
NSTO(WAA)	43.052	14.000	85.000	44.000
Mean	40.67			
Standard Dev.	$2.06 / \sqrt{10} = 0.65$			
Expected Value	41.84			

Table 5-1.

Off Site_Ta is the age of the waste when it departs the system, simulating its removal from the WAA. When each container is created it is “stamped” with the time that it was created. The age is calculated when it leaves the system as the elapsed time from creation to disposal. NSTO(WAA) is the number of containers in storage in the simulated WAA. The average number in storage is computed using the number of containers in storage as well as the amount of time that those containers were in storage; it is a sample average of the number of containers in storage at the beginning of each time unit. This is, therefore, a time weighted average over the course of the simulation run. In Table 5-1, we see that the simulation results in an average value for age of waste at removal from the WAA (Off Site_Ta) and long run average number of containers in storage (NSTO(WAA)) that are very close to those values found by applying the mathematical model from Chapter III. The standard deviation of the estimated mean for average age over the 10 runs was $0.33/\sqrt{10} = 0.10$, with the expected value from the mathematical model greater than 2 standard deviations above the simulation mean age. The standard deviation of the estimated mean average number of containers in storage over the 10 runs was $2.06/\sqrt{10} = 0.65$, with the expected value for containers in storage found using the mathematical model within 2 standard deviations of the simulation model’s mean number of containers in storage. The simulation model results compare favorably with those obtained using the mathematical model for the average number of containers in storage, but slightly underestimates age of wastes at disposal.

The values for simulated age of waste at disposal which are greater than 90 days occur due to the hypothesized distribution of waste service times. It is recognized that efforts taken in the “real-world” system would reduce these values. They are sufficiently

rare, however, that the effect of allowing the model to achieve long service times has minimal effect on the outcome.

The simulation was run 10 times, starting the inventory simulation at a different point in a random number sequence each time. The system begins empty, so the data from the first 500 days of simulated time is discarded to remove initial condition effects. This is often called a model's "warm-up" time. The data for the following 1000 days of simulated time are then used to compute the values in Table 5-1. At the beginning of every model "week," a random number of containers of waste arrives to the simulated storage facility. The storage facility will contain the highest volume of waste for that week after the arrival occurs and before a shipment can go out. This will be referred to as the facility's "weekly peak storage", and is the data of interest when considering the amount of storage capacity that will be required. This data is written to a file for later analysis.

The simulation model allows us to examine the "virtual" number of large containers that are in the WAA at any given time. The average number of large containers in the WAA given in Table 5-1 is the average over the period of the model runs, but we can observe the actual demand for storage space by writing out to a file the "virtual" inventory of containers in the WAA at specified times. Since we are concerned with capacity constraints, we record the values of the weekly peak storage to a data file that can be later recalled into a Microsoft Excel [Microsoft Corporation, 1985-1995] spreadsheet.

B. Zone 1, Small Wastes, "Old" System.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

Zone 1 Small Container Simulation Results				
TALLY VARIABLES (Simulated Age of Waste at Disposal)				
Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	35.913	15.500	134.50	573
Off Site_Ta	35.530	15.500	134.50	599
Off Site_Ta	33.964	15.500	120.50	588
Off Site_Ta	35.285	15.500	120.50	582
Off Site_Ta	34.990	15.500	183.50	612
Off Site_Ta	36.614	15.500	141.50	731
Off Site_Ta	35.199	15.500	162.50	732
Off Site_Ta	36.180	15.500	162.50	700
Off Site_Ta	35.241	15.500	176.50	595
Off Site_Ta	36.478	15.500	148.50	642
Mean	35.54			
Standard Dev.	0.79			
Expected Value	35.60			
DISCRETE-CHANGE VARIABLES (Simulated Number of Containers in Storage)				
Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	20.525	6.0000	58.000	13.000
NSTO(WAA)	21.220	6.0000	58.000	15.000
NSTO(WAA)	20.032	6.0000	48.000	14.000
NSTO(WAA)	20.533	5.0000	63.000	20.000
NSTO(WAA)	21.483	3.0000	53.000	10.000
NSTO(WAA)	26.646	9.0000	61.000	15.000
NSTO(WAA)	25.865	7.0000	65.000	20.000
NSTO(WAA)	25.307	5.0000	67.000	27.000
NSTO(WAA)	21.375	5.0000	55.000	25.000
NSTO(WAA)	23.404	7.0000	56.000	20.000
Mean	22.64			
Standard Dev.	2.47			
Expected Value	23.04			

Table 5-2.

In Table 5-2, we see that the simulation results in an average value for age of waste at removal from the WAA (Off Site_Ta) and average number of containers in storage (NSTO(WAA)) that are very close to those values found by applying the mathematical model from Chapter III. This indicates that the simulation model is operating as designed.

The results from simulating the small containers in the storage facility can now be added to the results from simulating the storage of large containers to give an idea of the total amount of storage space required to house these wastes.

C. All Waste Containers for Zone One

Converting all large containers to an equivalent number of 5 GCEs allows us to look at the total amount of storage space required for all wastes. Recall that the total storage space in 5GCEs is:

$$\text{TOTAL}_{5\text{GCEs}} = (3 * \text{Number of Large Containers}) + (1 * \text{Number of Small Containers}) \quad (5.1)$$

Plotting the weekly peak storage over the period of a simulation run shows the rise and fall of the “virtual” inventory level as time passes. The graph representing the inventory level over time from a single run is shown here (see Figure 5-2).

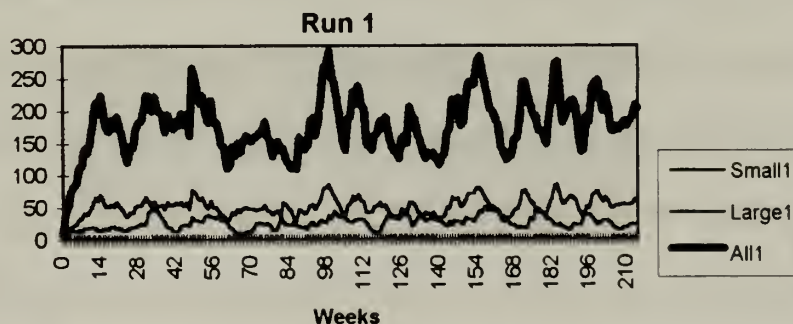


Figure 5-2.

The expected value for total storage space demanded under the “Old” System, calculated by using the mathematical model, is (148.56) 5 GCEs of storage space. The simulation resulted in a mean of (144.65) 5 GCEs of storage space. Additionally, we can compute the standard deviation of the mean as follows:

Let: \bar{X}_L be the mean number of large waste containers in storage.

\bar{X}_S be the mean number of small waste containers in storage.

$$\text{Then } \text{VAR} [(3 * \bar{X}_L) + \bar{X}_S] = 9 * \text{VAR}(\bar{X}_L) + \text{VAR}(\bar{X}_S). \quad (5.1)$$

Using the value from the preceding tables, we see that the standard deviation for the average value equals 2.10, and our simulation mean for total waste in storage are within 2 standard deviations of the expected value found using our mathematical model.

More importantly, however, we can now determine what amount of storage capacity we will need to maintain given a certain level of risk (a probability that we will exceed that capacity).

Our amount of available space is our commodity of interest. This available space is essentially our inventory, which has its level drawn down by the demand for space by waste containers arriving to the system. If the cost of exceeding the maximum waste storage capacity could be determined, commonly referred to in inventory control theory as a “stockout cost” [Tersine, pg. 214], then an optimal level of risk could be determined (given other associated inventory costs also known). Stockout cost is the sum of all costs that could be incurred due to an inability to meet demand; in our case it is the demand for extra storage space to hold material. This could be related to the financial effect of having to expedite an outgoing shipment to make space available, or the goodwill cost of having

a generator hold his waste at his laboratory for a few days, or the cost associated with having to store wastes in another zone's storage facility that does have space available, or other real and perceived costs. While a dollar value will not be assigned, LLNL places a high cost on stockouts, and therefore will accept only a small degree of risk.

The weekly peak storage demand (in 5GCEs) can be graphed as a histogram with the associated cumulative probabilities of occurrences below that level overlaid on the graph. The results from a single simulation run is provided here as Figure 5-3. The frequency (left Y axis) is the number of weeks that the given range of 5GCEs of storage space (the X axis) was required to store our "virtual" inventory.

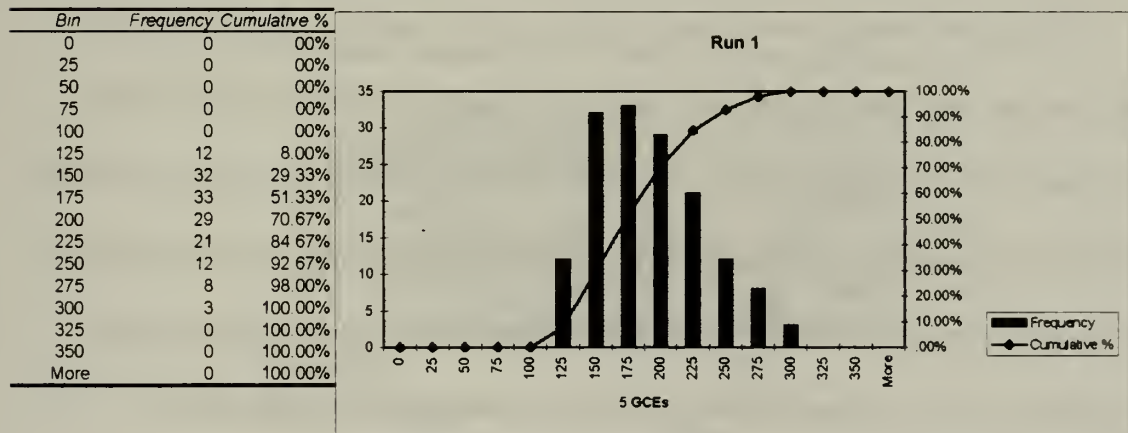


Figure 5-3.

The inventory levels associated with the 80%, 90%, 95%, and 99% cumulative probabilities will be given for each Zone and percentage of material assumed to be pre-classified, as well as the MAX Observed weekly peak demand for simulation runs. Our level of risk is equal to the probability of incurring a stockout at a given storage capacity, or 1 minus the cumulative probability at that storage capacity. The values associated with Zone 1 weekly peak storage values at these probability levels is given here as Table 5-3.

Inventory Level (in 5GCEs) Corresponding to Given Probability

Run	80%	90%	95%	99%	Max Observed
1	216	241	261	281	292
2	193	211	227	244	248
3	196	215	228	246	251
4	212	245	269	316	338
5	204	220	238	249	255
6	192	220	268	318	321
7	206	232	246	281	298
8	196	222	240	267	267
9	213	238	256	289	306
10	211	222	241	253	257
Average	203.90	226.60	247.40	274.40	283.30
Standard Dev.	9.04	11.61	15.38	27.53	32.09

Table 5-3.

A risk averse manager would assign a high cost to a stockout, and therefore be willing to accept only low levels of risk. Since a stochastic demand system always has some probability of exceeding capacity, we could choose a capacity level which represents the ability to meet weekly peak storage demand for 95% of the weeks, a 5% level of risk. It should also be noted that this inventory level is usually only encountered for a short period of time. Given this level of acceptable risk, we see that we would require approximately 247 5GCEs of storage space to accommodate the waste. Since this model assumes waste is being handled under the “Old” system, when no wastes are pre-classified by WEF, we would also have to be able to accommodate all of this waste outside of the 612-4 facility, which is still regulated by a RCRA permit.

D. SIMULATING THE NEW SYSTEM

1. Description of the Model

Under the “New” system, the amounts of waste arriving each week are expected to remain the same. The WAA, however, will now have additional tasks to perform on the hazardous waste. Some portion of the incoming hazardous waste will be classified on a Waste Evaluation Form prior to its arrival, allowing these containers to avoid standard service. The amount of time that it takes to process state and federally regulated wastes remain unchanged. Additionally, the weekly waste run has been replaced with more frequent shipments of waste from the WAA, which is estimated as twice per week.

A graph of this model constructed in Arena is shown as Figure 5-4.

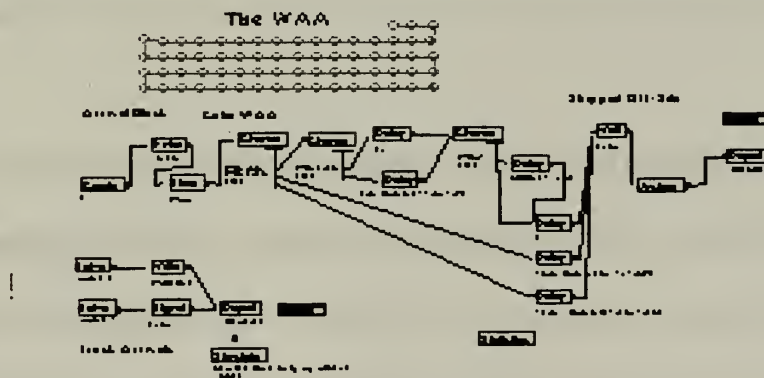


Figure 5-4.

The model can again be read from left to right like a flowchart. Again, wastes are “Created”, they “Enter” the WAA, and are then “Stored.” Again, each container travels through the system independently once created, and are initially all of a generic class of waste. In this model, a “Chance” node immediately after storage again assigns each container to a waste class. State and Federally regulated wastes go directly to traditional service, since the process for handling these wastes remains essentially unchanged.

Hazardous wastes are handled by another “Chance” node, which allows for the percentage of waste which arrives classified by a WEF to skip the traditional technician service, instead undergoing a delay of zero. Whether a hazardous waste is covered by a WEF or not, 10% (chosen at random) will undergo chemical analysis, the time being normally distributed with a mean of 14 days and standard deviation of 3 days. This can be viewed as a binomial distribution, with probability 0.10 and the number of trials being the number of containers generated that week. Hazardous wastes then get manifested to a hazardous waste disposal company, which takes 7 days to perform. The total delay time for each container is independent of other containers. All wastes must “Wait” for a truck once service is complete. Trucks are scheduled to arrive twice a week, at which point all wastes that have completed service are “Unstored” from the WAA and “Depart” the system.

Another modification is in the data collection for material in the WAA. Since the previous model allowed for weekly shipments, the inventory could be examined after delivery of a week’s waste and just prior to the week’s outgoing shipment to give a peak load in the WAA during that week. With two shipments going out per week, a separate “Arrive” node signals the model to “Write” the data once per week, at this desired peak loading point, to an output file.

2. An Example of Simulation Results, Zone 1.

The amount of waste classified by WEF can be varied in this model, and the initial runs were conducted with the percentage of waste that is pre-classified set to 0%. This

indicates the results of changing the handling system without being able to pre-classify any wastes, and results in the highest inventory levels.

Again, we will start by verifying that the simulation model is behaving as expected by comparing the long-run results from simulation with our expected values derived by the mathematical model. For these runs, the maximum software storage limit of 100 entities was exceeded. Therefore, the number of containers arriving each week was cut in half to avoid exceeding this constraint, and the resulting number of entities stored in the WAA represent one half of the actual inventory for these items. A close approximation to the true value can be obtained by multiplying the number of entities stored by two. See Table 5-4.

TALLY VARIABLES (Simulated Age of Waste at Disposal)				
Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	36.158	19.000	145.00	697
Off Site_Ta	35.908	19.000	117.00	704
Off Site_Ta	35.651	19.000	117.00	726
Off Site_Ta	36.294	19.000	131.00	697
Off Site_Ta	36.318	19.000	159.00	657
Off Site_Ta	35.832	19.000	159.00	692
Off Site_Ta	35.713	19.000	148.50	783
Off Site_Ta	37.057	19.000	145.00	734
Off Site_Ta	36.104	19.000	127.50	682
Off Site_Ta	35.918	19.000	127.50	620
Mean	36.095			
Standard Dev.	0.408/ $\sqrt{10}$ = 0.13			
Expected Value	36.75			
DISCRETE-CHANGE VARIABLES (Simulated number of Containers in Storage)				
Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	24.899	12.000	41.000	32.000
NSTO(WAA)	24.907	8.0000	53.000	22.000
NSTO(WAA)	25.873	8.0000	53.000	41.000
NSTO(WAA)	24.884	9.0000	47.000	26.000
NSTO(WAA)	23.964	7.0000	45.000	31.000
NSTO(WAA)	24.782	11.000	49.000	23.000
NSTO(WAA)	27.653	12.000	51.000	26.000
NSTO(WAA)	27.099	9.0000	49.000	19.000
NSTO(WAA)	24.642	9.0000	52.000	28.000
NSTO(WAA)	22.728	8.0000	47.000	47.000
Mean	25.14			
Standard Dev.	1.43/ $\sqrt{10}$ = 0.45			
Mean * 2	50.28			
Exp. Value / 2	25.54			
Expected Value	51.08			

Table 5-4.

The standard deviation for the mean number of containers in the unscaled model is 0.90, and our unscaled mean from the simulation is within 2 standard deviations of the expected value found using the mathematical model.

Again, the “virtual” inventory levels of peak weekly storage demand were saved to a file for each simulation run. Combining the inventory levels for small and large containers in common units, 5GCEs, allowed for computing the inventory level associated with our chosen level of cumulative probability for meeting weekly peak demand. The values associated with Zone 1 weekly peak storage values at these probability levels, when it is assumed that no waste is being pre-classified by WEF, is given here as Table 5-5.

Inventory Level (in 5GCEs) Corresponding to Given Probability

Run	80%	90%	95%	99%	MAX Observed
1	204	219	235	262	283
2	224	245	274	330	341
3	241	258	290	315	322
4	266	282	296	333	337
5	228	247	268	295	289
6	225	243	262	300	308
7	249	278	296	322	319
8	240	271	312	362	375
9	239	254	283	344	354
10	223	241	252	270	273
Average	233.9	253.8	276.8	313.3	320.1
Standard Dev.	16.99	19.18	23.23	31.76	32.66

Table 5-5.

As expected, when it is assumed that no wastes can be pre-classified by WEF, the inventory levels will increase over those observed for the “Old” system. The extra time to service the waste causes this increase. The remaining individual simulation run results are left to Appendix C, with the overall results shown next.

E. RESULTS OF THE SIMULATION MODEL

The simulation model was applied to each zone's consolidating facilities separately, under assumptions of increasing percentages of hazardous waste being able to be pre-classified by WEF. While the mathematical model described in Chapter III demonstrated that the long run average quantities of waste in storage would decrease, it was the goal of using the simulation model to determine the effect on peak demand for storage space. Whenever a system incurs stochastic demand, there is always some probability that the system will not be able to meet the demand. Therefore, the manager seeks to find a point where the probability that he will not be able to meet the demand is small, or at least cost effective. If exceeding demand for short periods of time does not incur significant cost, it may be acceptable to have this happen more frequently.

The simulation model incurs weekly peak demand immediately after a delivery of that week's waste arrives in the system, and this peak demand remains until the next shipment goes out. This means that the weekly peak demand does not necessarily last the entire week, but rather lasts until material is shipped out.

The results for the simulations give a result based on a certain level of acceptable risk. Since meeting the generators' needs is important, it can be assumed that we desire to meet those needs by accepting only low levels of risk. The results from the model for meeting weekly peak demand for 95% of weeks (Table 5-6.) and for 99% of weeks (Table 5-7) are given here. Displayed are the means of the 95th (respectively 99th) quantile of the empirical distributions for weekly peak demands for 10 replications of the simulation. Appendix C includes additional information on maximum levels encountered during the

simulation runs, which would be the most risk averse standard of measure, as well as results for managers desiring to incur greater risk.

Mean of the 95% Quantiles of Weekly Peak Inventory Levels (in 5GCEs) for 10 Simulation Replications.

Zone	"Old" System	0% WEF	25% WEF	50% WEF	75% WEF
1	247.4	276.8	247.3	188.1	162.9
2	68.7	75.2	63.3	56.6	46.8
3	84.7	94.7	84.4	74.8	58.1
4	374.6	402.2	353.5	294.4	246.2
TOTAL	775.4	848.9	748.5	613.9	514

Table 5-6.

Mean of the 99% Quantiles of Weekly Peak Inventory Levels (in 5GCEs) for 10 Simulation Replications.

Zone	"Old" System	0% WEF	25% WEF	50% WEF	75% WEF
1	274.4	313.3	278.6	225.1	199.1
2	76.3	85.3	72.3	63.4	55.6
3	95.8	105.0	98.0	86.2	68.8
4	398.5	420.5	377.3	320.1	271.0
TOTAL	845	924.1	826.2	694.8	594.5

Table 5-7.

Tables 5.6 and 5.7 clearly demonstrate the effect that increasing percentages of pre-classified waste have on peak inventory levels. While the trend of the effects on peak inventory levels is the same as the effect on long-run average inventory levels, the magnitude of the effect is clearly not. In Chapter III, it was shown that changing to the "New" system, and assuming that no waste could be pre-classified, would increase the average demand for storage space by approximately 14%, but at these higher quantiles of the distribution of weekly peak storage levels, the increase is under 10%. Additionally, we now have an estimate for what the estimated peak demand will be under varying conditions, which the mathematical model could not provide.

If all storage facilities were able to handle all wastes (whether pre-classified by WEF or not), then the above values can be used to directly approximate the required capacity that must be kept available. However, the approximation that 50% of hazardous wastes arriving to the WAA pre-classified by WEF does not indicate that this material will consume 50% of required storage space. Rather, at any given time the percentage of material in storage that is pre-classified by WEF will be lower than this percentage since these wastes remain in storage for shorter periods of time.

Again, we can refer to expected value methodology to approximate the percentage of storage space in use by pre-classified waste. Let us consider W_{WEF} to be the average amount of time that a container that has been pre-classified by WEF remains in storage awaiting disposal. Let us consider W_{WASTE} to be the average amount of time that all containers of waste remain in storage awaiting disposal. Additionally, let us consider λ_{WEF} to be the arrival rate of pre-classified wastes, which is some percentage of λ_{WASTE} , the arrival rate for all wastes. We can see that the percentage of waste in storage that is pre-classified by WEF will be equal to

$$(\lambda_{\text{WEF}} * W_{\text{WEF}}) / (\lambda_{\text{WASTE}} * W_{\text{WASTE}}) \quad (5.2)$$

This can be seen as the expected quantity of pre-classified waste in storage divided by the expected quantity of all waste, each found using Little's Formula [Ross, pg. 353]. This type of methodology was described more fully in Chapter IV.

In three of the four zones, traditional ("WEFable") hazardous waste makes up less than 100% of the total waste containers arriving for storage in these facilities and storage

times for pre-classified waste is always shorter than storage times for wastes not pre-classified.

For example, in Zone 1 we see that this formula can be readily applied for 50% of the hazardous waste arriving to the WAA pre-classified by WEF. Referring to Appendix B, Table B-4, we see that (in 5GCEs) $\lambda_{\text{WEF}} = (0.5) * (4.53 + 29.19) = 16.86$. Total arrivals are $\lambda_{\text{WASTE}} = 33.72$ (in 5GCEs). This is 50% of arrivals, since State and Federally regulated wastes do not constitute a portion of the waste generated in this zone. However, the average service time for a pre-classified waste container is 10.15 days, while the average service time for all wastes (including pre-classified waste) is 22.14 days. Using (5.2), we therefore compute that the average percentage of waste in storage that arrived pre-classified by WEF is only about 23% of the average total waste in storage.

This makes sense intuitively. Recognizing that the service time for a waste that is not pre-classified by a WEF (demonstrated using the 0% WEF model shown in Table B-2) is over 3 times as long as the service time of a pre-classified waste, three pre-classified waste containers could enter and leave the facility in the time it takes to service one container that was not pre-classified. Given equal quantities of waste arriving in a pre-classified and not pre-classified state, and a significantly shorter service time for the pre-classified wastes, then the percentage of pre-classified waste in inventory must be less than one half.

When also dealing with state and federally regulated wastes sharing the same storage area, it is evident that the long service times associated with these wastes will drive the percentage of waste in storage that is not pre-classified by WEF even higher. We can use the 23% value derived above, however, as an estimate for the percentage of

materials that could go directly into the 612-4 facility while meeting the requirements of the RCRA permit for waste characterization.

If we consider meeting peak storage demand 95% of the time to be a conservative approach to choosing our desired end capacity for storage, and we assume that 50% of hazardous wastes will arrive at storage facilities pre-classified by the generator through use of a WEF, we can estimate that we could route approximately 141 units of storage demand (23% of the 613.9 units shown in Table 5-6) directly to the 612-4 facility but must maintain the remaining 473 units of storage capacity through other Consolidation WAAs which are not constrained by a RCRA permit.

Based on the current estimate of maintaining only the WAA 169 and WAA 361 facilities as available to receive this waste, with a combined capacity of 244 5GCEs of waste, it becomes apparent that we could often exceed our capacity for storage of “un-WEFed” waste. There are several solutions to this situation, which will be the focus of the next chapter.

VI. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

A. SUMMARY

Chapters I and II describe the current Hazardous Waste Management re-engineering process being undertaken at LLNL, as well as some of the impetus behind the actions. Chapter III and Appendix A present the results of analysis of historical data pertaining to the waste generation rates and service time. Additionally, a common unit for waste storage was provided, the "5 gallon container equivalent" or 5GCE. This information was necessary to develop a model of the waste management process. The mathematical model presented in Chapter IV demonstrates the effect that the re-engineering is expected to have on long-run average amounts of waste in storage, based on varying degrees of success in meeting waste pre-classification goals. While this information gives insight into how the re-engineering will aid in decreasing the demand for storage, it does not deal with the more central issue of how much waste storage capacity is truly needed. The goal of the re-engineering is to take steps that will allow for reducing the amount of storage facilities in use, without risking a need for later reopening storage facilities.

In Chapter V, a commercially available simulation package, *Arena*, was used to construct a representation of the waste management process. The results of the model indicate the effect of the re-engineering on weekly peak inventory levels, the data of interest. Additionally, the model can be modified in the future to examine how additional modifications to the waste handling processes would affect these levels.

B. CONCLUSIONS AND RECOMMENDATIONS

By closing a large number of small storage facilities and routing this waste instead to a few large, consolidated storage facilities, the re-engineering process is projected to cut annual waste management costs at LLNL. A list of facilities targeted for consolidation is provided in Table 2-1. The closure of these 24 WAA facilities will result in a total decrease in available storage capacity of 1156 5GCEs. We can assume a risk averse strategy would desire to ensure the ability to meet peak demand for 95% of the weeks, or possibly even greater percentages of the time. Based on the estimate that 50% of the wastes entering these facilities will be pre-classified by WEF under the new system, we see in Table 5-6 that the peak inventory levels of the Consolidation WAAs would seldom exceed 614 5GCEs of storage space at this level of risk. Since the processing times for wastes that are not pre-classified by WEF are much longer than processing times for "WEFed" waste, it was demonstrated using equation (5.1) that most of this space would be required to store wastes which could not be pre-classified. Noting that facility 612-4 is currently maintained as a RCRA permitted facility, only those wastes that are pre-classified could be sent directly to that facility. The remaining containers of material would have to be routed to the two other planned consolidation facilities, WAA 169 and WAA 361. Since they can accommodate only 244 5GCEs of waste, the simulation model indicates that these facilities would very likely experience periods when they could not meet the demand for storage of waste.

There are various options available to remedy with this. One would be to ship wastes out of the Consolidation WAAs more often under the "New" process than under the "Old." There are two ways to view this option. Either these shipments will have to be

sent off-site more frequently (which directly implies that each outgoing shipment will contain less waste), or materials that are awaiting shipment may have to be transferred into the permitted facility during high demand periods. Increasing the frequency of outgoing shipments may be acceptable if the cost of the extra shipments is offset by annual savings of closing additional facilities. Likewise, the on-site transfer of wastes from WAA 169 and WAA 361 to the 612-4 facility during high periods of storage demand may be acceptable if the cost of double handling of waste on site is low. One goal of re-engineering, however, was to ship the wastes directly from the Consolidation WAAs.

Alternatively, additional facilities could be kept open until the percentages of waste able to be pre-classified by WEF is increased. The best candidate for this is WAA 511, which has an ORAD capacity of 180 5GCEs, greater than either WAA 169 or WAA 361. Even increasing the storage capacity by this amount does not completely fill the shortfall, but does bring available capacity levels to an amount for which there is a lower risk of overloading the storage capacity.

Another option is to work toward increasing the percentage of waste coming from the generator fully classified by WEF and containerized for shipping. By increasing the WEF percentage, we are less likely to exceed our finite capacity in two ways. First, since the average time to process waste is decreased, the peak quantity of waste at various levels of risk decreases. Second, and more importantly, more wastes could be routed directly to the 612-4 facility.

If, however, the implementation of the WEF has made the 90 day timeline for wastes being stored in the WAA now able to be achieved for **all** hazardous wastes (rather than just the waste actually pre-classified by the WEF), the most viable alternative would

be to reclassify the 612-4 facility as a WAA, removing the RCRA permit. This allows for a significantly larger storage capacity for wastes coming straight from the generator, without requiring the pre-classification of wastes prior to entering the facility. In fact, the simulation results indicate that this facility alone could handle all the wastes from the closing facilities with virtually no risk of exceeding capacity. This would allow for closing WAA 169 and WAA 361, and maintaining 612-4 as the single hazardous waste storage facility for receipt of wastes from those facilities listed in Table 2-1.

There are some additional risks associated with having 612-4 as the single hazardous waste storage facility not directly related to the methodology described in this thesis. For example, if items are unable to meet the 90 day timeline for off-site shipment, there would no longer be a permitted facility to hold these wastes for extended periods of time. This may not be a point of interest, however, since wastes that would take this extended period of time to classify may not be included under the current RCRA permit anyway. However, in a laboratory setting there are expected to be occasions when atypical wastes require extensive efforts to dispose. Another risk is that if a hazardous condition (such as a spill) were to occur in the 612-4 facility, there would be no alternative place to route generated wastes to while corrective action was being taken.

In conclusion, the re-engineering process attempts to close a large quantity of underutilized storage facilities through a well thought out series of steps. The goals of the project are not just to pick the "low-hanging fruit" but rather to eliminate as much unneeded capacity as is feasible. The decrease in average storage needs able to be achieved are obvious. However, decreasing storage capacity is not without some risk. The simulation model formulated in this thesis indicates that there may be a periods of

time when extra measures will be required to ensure that capacity of facilities is not exceeded under the given assumptions. However, the magnitude of the results may be sensitive to the assumptions concerning the tails of the distributions of service times.

Additionally, the simulation model demonstrated here can be adapted in the future to look at the feasibility of closing additional facilities, increasing the percentage of pre-classified wastes, increasing the frequency of shipments, or decreasing the time to perform various service related tasks. By utilizing a simulation such as the one developed in this thesis, a manager can perform his own “what if ...” changes to the simulated system. By approximating the effect on the real world system, he can determine if the process change is worthwhile without incurring the high cost of modifying the real world system.

APPENDIX A : DATA ANALYSIS

A. INTRODUCTION

In this appendix, the procedures described in chapter three are applied to the remaining zones and waste types. Wherever possible, a graphical representation has been provided to allow the reader to visualize the reasoning behind certain routes that the analysis has taken. This appendix in no way purports to be a tutorial in data analysis, but is rather meant for clarification and documentation for the analysis used to support the findings of this thesis.

One facet that will be explained is the use of continuous distributions to describe discrete data. The number of containers of a given size arriving to the WAAs are modeled by a random draw from a distribution, either empirical or theoretical. When an empirical distribution is used to model the arrivals, a finite number of discrete values can be achieved, each with a specific probability. While this is an exact representation of the data, it does not allow the arrival process to achieve values in the future that have not been achieved in the past. It is also often cumbersome to work with empirical distributions when using a simulation tool such as Arena since the empirical cumulative distribution function (CDF) of the number of containers arriving per unit time must be programmed into the arrival process. Modeling the arrivals according to a well defined, and well fitting, common distribution overcomes these difficulties, but is not without its own difficulties. Since the common distributions used are continuous functions, there must be a way to choose an appropriate integer value based on the result of a random

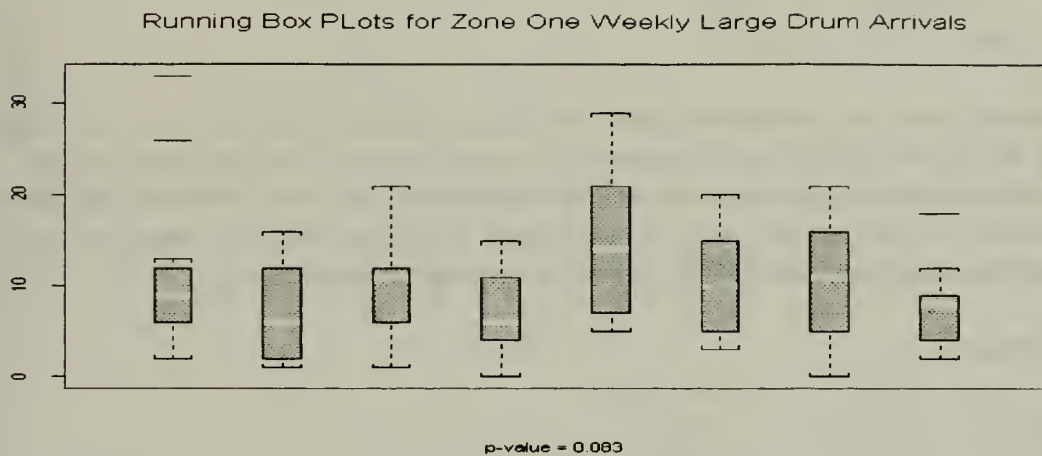
draw from the hypothetical distribution. The way that the simulation program performs this choice may affect the result of the simulation and must be determined.

The exact means that Arena uses to choose the number of arrivals from the hypothetical distribution could not be found in the documentation provided. Through testing it was determined that Arena chooses its random draw from the hypothetical distribution, and then truncates the real valued result to give a discrete number of arrivals. A random draw indicating (1.1) or (1.8) arrivals both result in (1) arrival occurring. This truncation causes the average value to be lower than expected. It would be preferable to have the random draw rounded to the nearest integer. Since rounding to the nearest integer is not incorporated into Arena, a method for rounding must be incorporated by the user. This was performed by adding 0.5 to the random draw prior to truncation. For the above example, a random draw of (1.1) becomes (1.6) and is truncated to achieve (1) arrival, while a random draw of (1.8) becomes (2.3) and is truncated to achieve (2) arrivals. The only drawback to this process is that the occurrence of (0) arrivals only can be achieved in a one-half integer range. Since the probability of achieving a zero is generally low, this does not cause significant departure from expected results. The small deviation that it does cause is an error toward a higher (pessimistic) estimate of the number of containers arriving in a given week.

1. Zone One:

A. Large Containers.

Arrivals per week:



Performing Analysis of Variance on the 8 non-overlapping time intervals, denoting the 8 quarters of waste arrivals analyzed, gives the following results:

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	146	11.23077	79.69231
Column 2	13	97	7.461538	33.10256
Column 3	13	129	9.923077	31.24359
Column 4	13	90	6.923077	22.07692
Column 5	13	183	14.07692	61.57692
Column 6	13	128	9.846154	33.97436
Column 7	13	143	11	45.5
Column 8	13	96	7.384615	21.58974

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	537.3846	7	76.76923	1.868112	0.083221	2.106468
Within Groups	3945.077	96	41.09455			
Total	4482.462	103				

With a p-value greater than 0.05, we cannot reject the null hypothesis that the mean number of containers arriving during a week changes is the same during each of the eight quarters.

Performing ordinary least squares regression (OLS) to fit a trend line to the data over time gives the following results:

Residuals:

Min	1Q	Median	3Q	Max
-9.86	-4.865	-0.728	4.678	23.26

The median value for residuals indicates two things. The data takes on a few very high values, which have significant influence on the mean number of arrivals, and the data cannot balance these high values because the data cannot take on values less than zero. This means that the residuals will not be normally distributed about the trend line, and detracts from the predictive quality of modeling using the trend line.

Coefficients:

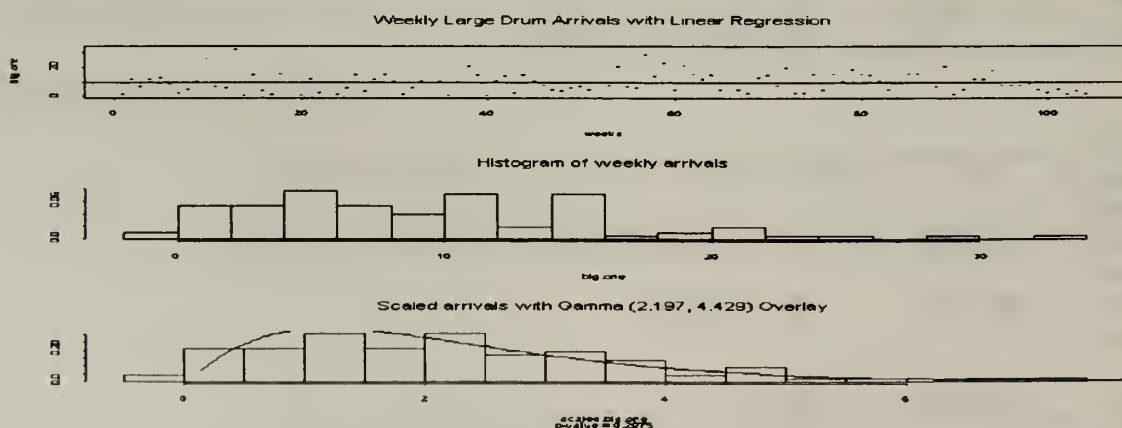
	Value	Std. Error
(Intercept)	9.7179	1.3135
weeks	0.0017	0.0219

Since the standard error of the coefficient on the independent variable (weeks) is greater than the value, we see that the value cannot be assumed to be different than zero, which is the same result that ANOVA gave us.

Residual standard error: 6.617 on 101 degrees of freedom

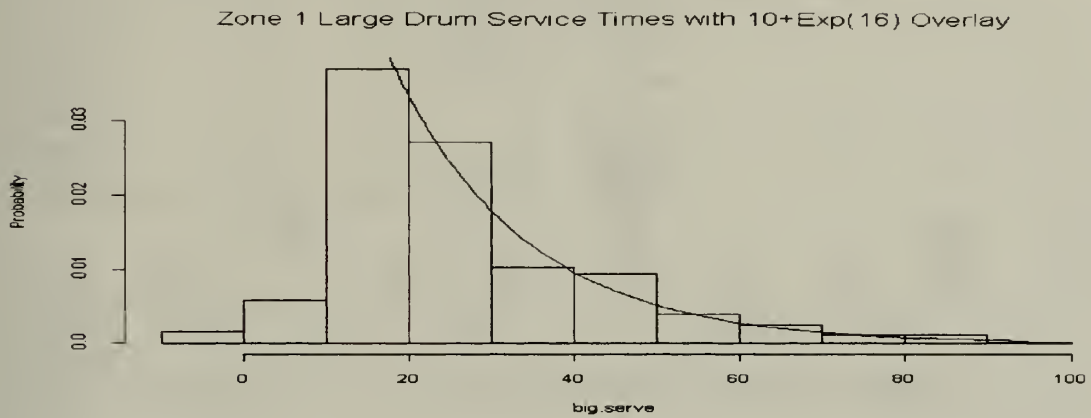
Multiple R-Squared: 0.0000589

Slope = 0.0017, over 104 weeks, indicating that there is no strong indication of time dependence in the data. The data can therefore be modeled as independent, identically distributed random variables from some distribution, which we model next.



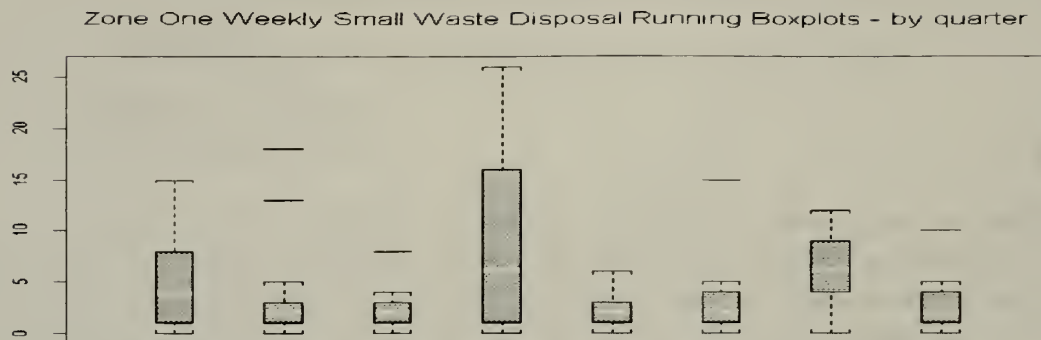
The results of the distribution fitting for the number of containers arriving each week of this waste are described in Chapter III.

The service times were also analyzed previously; below is the graphical result of overlaying the hypothetical distribution best fitting the data on the histogram of service times, in days, from the data.



B. Small Containers:

Arrivals per week:



Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	66	5.076923	18.24359
Column 2	13	51	3.923077	29.07692
Column 3	13	35	2.692308	7.064103
Column 4	13	122	9.384615	94.75641
Column 5	13	32	2.461538	2.602564
Column 6	13	52	4	26.83333
Column 7	13	78	6	13.33333
Column 8	13	35	2.692308	7.064103

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	490.2212	7	70.03159	2.815703	0.010357	2.106468
Within Groups	2387.692	96	24.87179			
Total	2877.913	103				

Analysis of Variance indicates that the means over the 8 quarters are probably not all equal. Looking at the graph of running boxplots, it appears that Qtr 4 may have a different mean value than the other 7 quarters. It is also noted that the variance observed in Qtr. 4 is also significantly higher than other quarters, which detracts from the usefulness of analysis of variance testing. The remaining 7 quarters do appear to yield similar results, and this can be verified by performing ANOVA on the data with Qtr 4 removed.

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	66	5.076923	18.24359
Column 2	13	51	3.923077	29.07692
Column 3	13	35	2.692308	7.064103
Column 5	13	32	2.461538	2.602564
Column 6	13	52	4	26.83333
Column 7	13	78	6	13.33333
Column 8	13	35	2.692308	7.064103

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	139.9121	6	23.31868	1.566244	0.167128	2.208552
Within Groups	1250.615	84	14.88828			
Total	1390.527	90				

The means of 7 of the 8 quarters do appear to be the same (excluding the fourth quarter), and ANOVA indicates that this cannot be disproved, with a resulting p-value of 0.167 for the hypothesis that $\mu_1=\mu_2=\mu_3=\mu_5=\dots=\mu_8$. This does not appear to adversely affect the trend line, which is essentially flat across the two year period, but may affect the mean number arrivals each week. During the fourth quarter, there were three weeks which experienced an abnormally high number of containers arriving (outliers), and this greatly increased the mean value and variance for arrivals during the quarter. Including this data may cause us to overestimate the number of containers arriving each week. We should not reject this data, however, since these abnormally high values indicate a possible source of disruption to the real world system, and should therefore be included in the model. There is no clear cause for the high demand during this quarter, however, so the arrival model will consider that this high rate could occur during any given week, and is not more likely to occur during any particular time period.

Performing OLS, we achieve the following results :

Residuals:

Min	1Q	Median	3Q	Max
-4.908	-3.53	-1.669	1.474	21.42

Noting that the Median residual is less than zero shows that there are a few cases that take on high values (which occur in Qtr 4, as noted by ANOVA).

Coefficients:

	Value	Std. Error
(Intercept)	4.9235	1.0587
weeks	-0.0075	0.0177

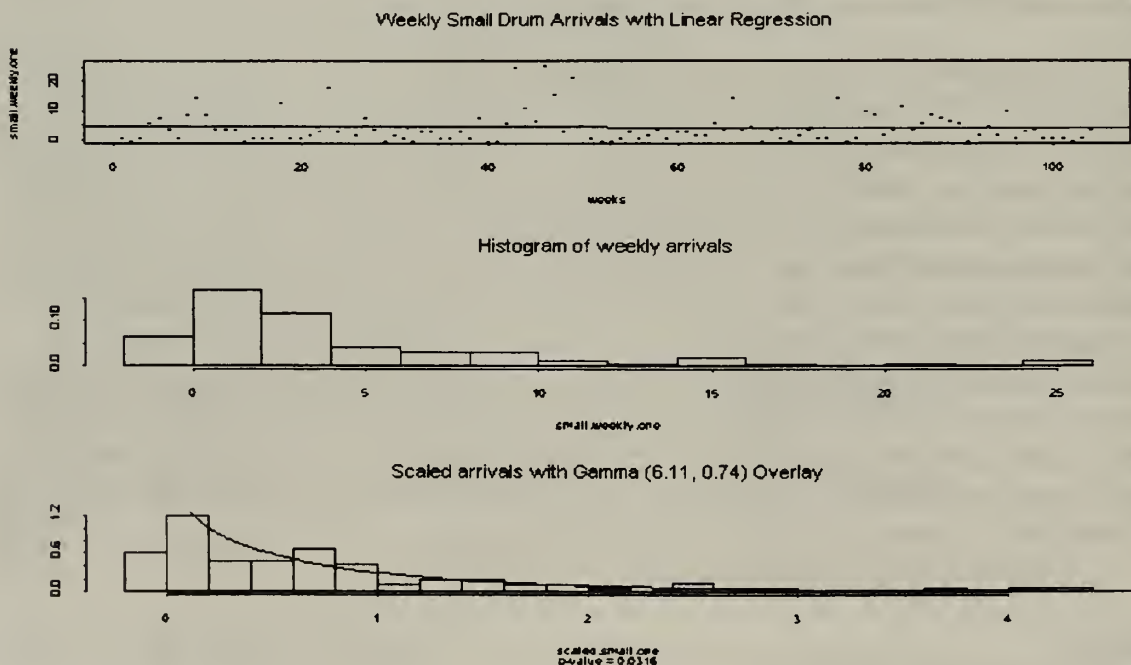
Again, the standard error of “weeks” is significantly higher than the estimate of the coefficient. The estimate is not significantly different from zero.

Residual standard error: 5.333 on 101 degrees of freedom

Multiple R-Squared: 0.001775

(Intercept) weeks
4.923472 -0.007490225

A slope of -0.0075 containers per week over the two year period indicates a total change of only 0.037 containers less being disposed each week. This represents a decrease of approximately 5% annually. This small value indicates that there is no strong evidence of time dependence in the data, and we may model the data as independent, identically distributed random variables from the estimated distribution.



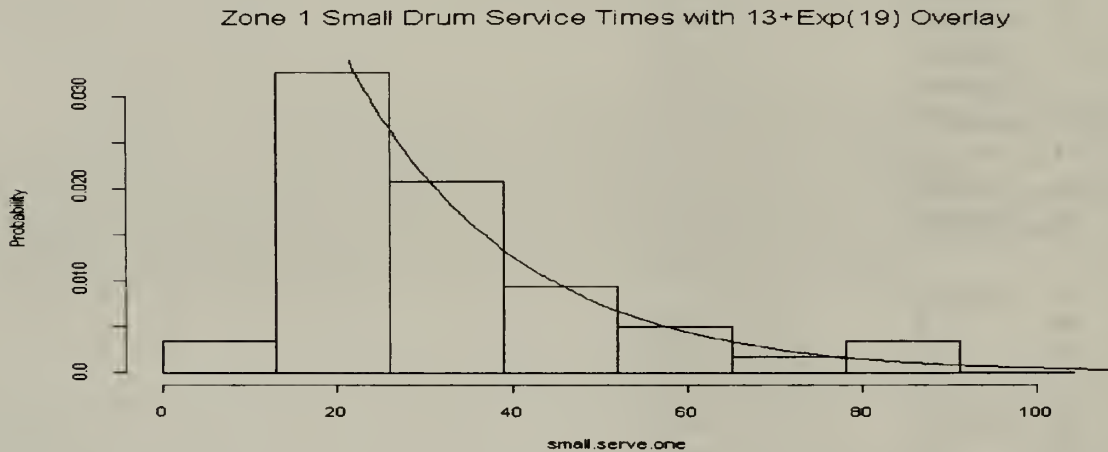
The frequency of a given number of containers arriving in any given week is denoted by the above histogram. The best summary for this empirical distribution was a gamma distribution with the parameters shown in the figure. Noting that the resulting p-value for the goodness of fit test was less than 0.05, the empirical distribution of the number of arrivals per week will be used.

Empirical Distribution:

Arrivals	pmf	Arrivals	cmf
0	0.125	0	0.125
1	0.240385	1	0.365385
2	0.096154	2	0.461538
3	0.096154	3	0.557692
4	0.134615	4	0.692308
5	0.038462	5	0.730769
6	0.048077	6	0.778846
7	0.019231	7	0.798077
8	0.038462	8	0.836538
9	0.038462	9	0.875
10	0.019231	10	0.894231
11	0.009615	11	0.903846
12	0.009615	12	0.913462
13	0.009615	13	0.923077
14	0	14	0.923077
15	0.028846	15	0.951923
16	0.009615	16	0.961538
17	0	17	0.961538
18	0.009615	18	0.971154
19	0	19	0.971154
20	0	20	0.971154
21	0	21	0.971154
22	0.009615	22	0.980769
23	0	23	0.980769
24	0	24	0.980769
25	0.009615	25	0.990385
26	0.009615	26	1

Service Times:

The service time, in days, for small containers of waste disposed in Zone One, is shown below with a curve demonstrating the shifted exponential approximation for these times; the shifted exponential distribution was the best summary for these data. There is a low percentage of waste which took less than 13 days to process with a sharp rise thereafter, indicating that using an exponential distribution to model service times would be appropriate. The result of using the square root of the variance from the actual data as the estimated rate parameter, and shifting the exponential to the right by 13 units to adjust the hypothetical distribution's mean, is shown below.

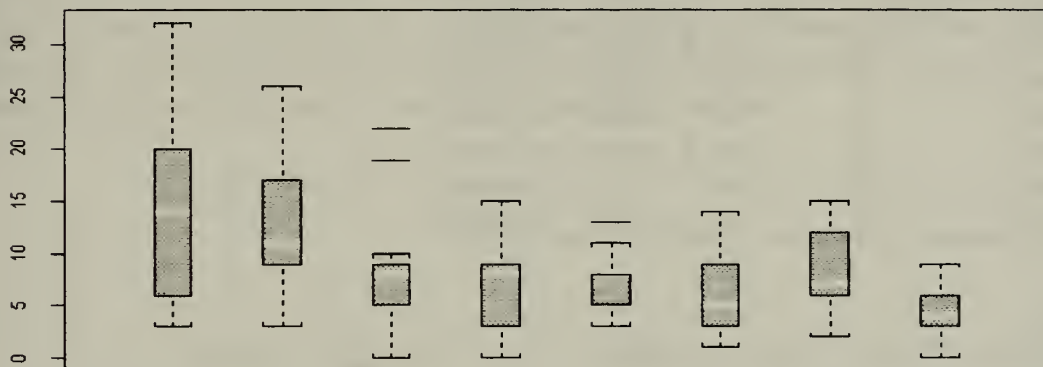


2. Zone Two:

A. Small Containers.

Arrivals per week:

Zone Two Weekly Small Container Disposals Compared by Quarter



Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	188	14.46154	89.4359
Column 2	13	159	12.23077	46.52564
Column 3	13	109	8.384615	37.25641
Column 4	13	92	7.076923	26.41026
Column 5	13	92	7.076923	8.576923
Column 6	13	80	6.153846	16.97436
Column 7	13	104	8	16.66667
Column 8	13	59	4.538462	7.435897

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	974.6058	7	139.2294	4.468172	0.000243	2.106468
Within Groups	2991.385	96	31.16026			
Total	3965.99	103				

Observing the $p\text{-value} < 0.05$ indicates that the means for the 8 quarters are not all equal. Looking back at the running boxplots, it appears that the first two quarters are indeed different from the last six. We therefore hypothesize that perhaps the last average weekly number of small containers being disposed over the past 6 quarters may be equal, and the arrival rates during that period can be used to predict following time periods. This is verified using ANOVA on the last 6 quarters' arrival data, as follows:

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	109	8.384615	37.25641
Column 2	13	92	7.076923	26.41026
Column 3	13	92	7.076923	8.576923
Column 4	13	80	6.153846	16.97436
Column 5	13	104	8	16.66667
Column 6	13	59	4.538462	7.435897

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	124.8718	5	24.97436	1.322322	0.264409	2.341828
Within Groups	1359.846	72	18.88675			
Total	1484.718	77				

So, we cannot reject the assumption that $m_3=m_4=\dots=m_8$. We will therefore use only the last six quarters of data for forecasting arrivals.

Performing OLS regression for the last 6 quarters yields the following results:

Residuals:

Min	1Q	Median	3Q	Max
-8.038	-2.97	-0.1287	1.518	13.72

Coefficients:

	Value	Std. Error
(Intercept)	8.4332	0.9894
weeks	-0.0395	0.0218

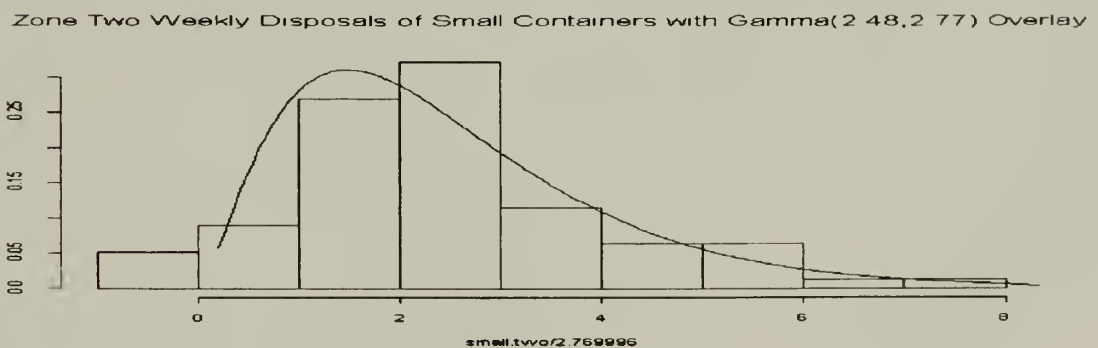
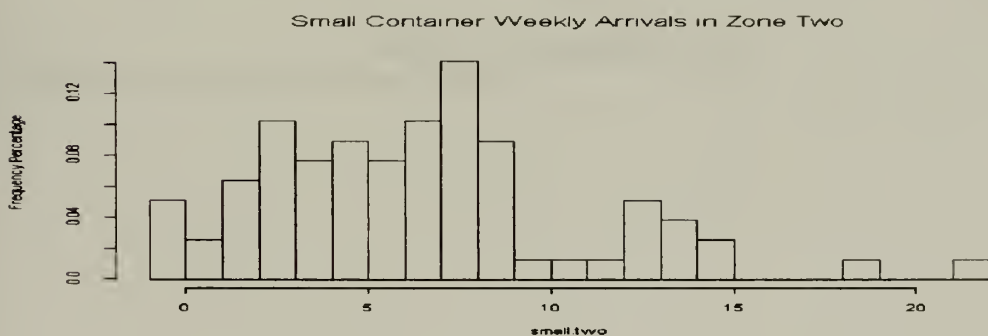
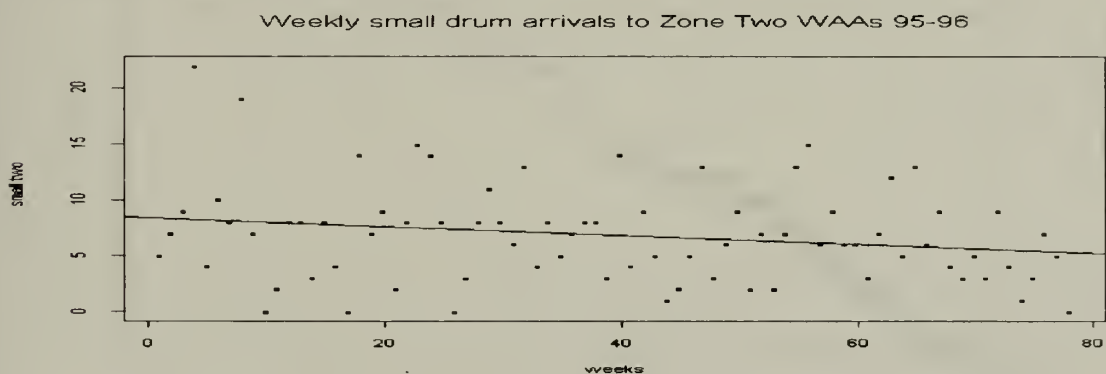
Again, with a comparatively large standard error, we cannot draw a conclusion that the slope is "significantly" different from zero.

Residual standard error: 4.327 on 76 degrees of freedom

Multiple R-Squared: 0.04161

Slope = -0.0395, which implies an annual decrease of approximately 24 % in the number of containers being disposed, but the large standard error indicates that the slope is not significantly different than zero.

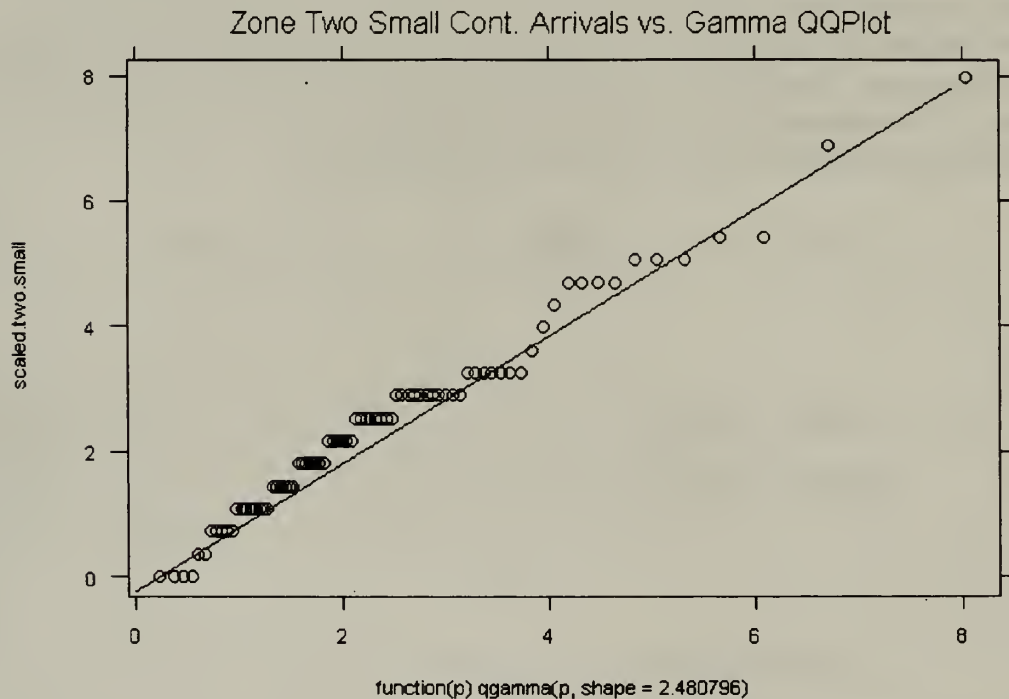
While the linear model exhibits a downward trend, ANOVA found no significance in the difference from one quarter to the next, so we will assume that the disposal quantities are consistent over time though fairly random for any given week, and will be able to be applied for the next time intervals. We will model the number of containers arriving each week as independent, identically distributed random variables drawn from the modeled distribution. The histogram for the number of containers arriving weekly is displayed. A Gamma distribution was found to be a good summary of the data.



Using Method of Moments, we find that the estimate for shape = 2.48, scale = 2.77. Performing KS Goodness of Fit yields a p-value of 0.3175.

A Quantile-Quantile plot, shown here, compares the quantiles of the empirical distribution to the hypothetical Gamma distribution found to best summarize the data. Noting that the plot closely follows a line with a slope of one shows that the gamma with the chosen parameters does indeed capture the shape of the empirical distribution.

Slight deviations are to be expected.



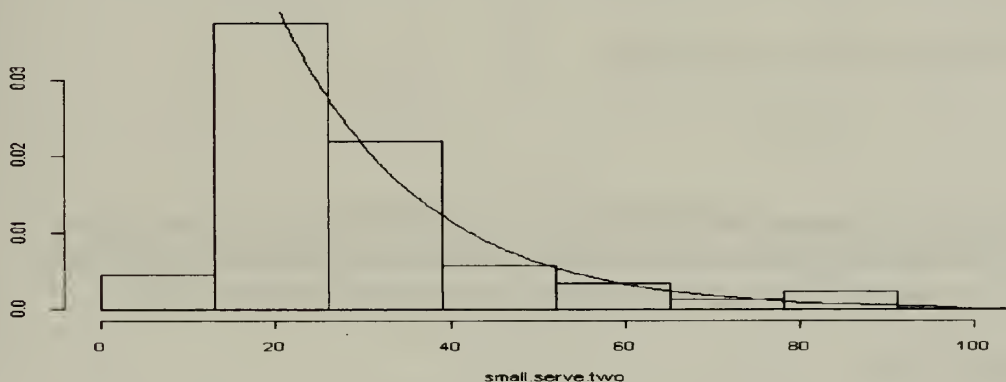
Service times:

Note that although earlier analysis indicated that only the last 6 quarters of small container arrivals should be used for modeling arrivals in Zone Two, it has been assumed that the quantity of waste coming into the WAA does not affect service time. We therefore use the entire data set for modeling service times.

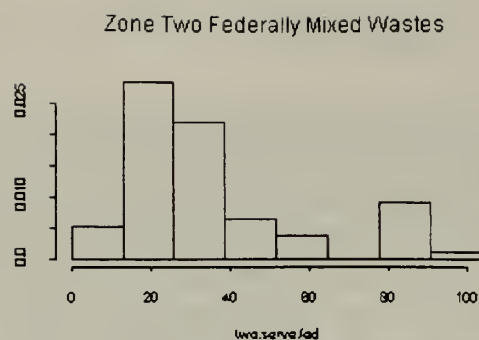
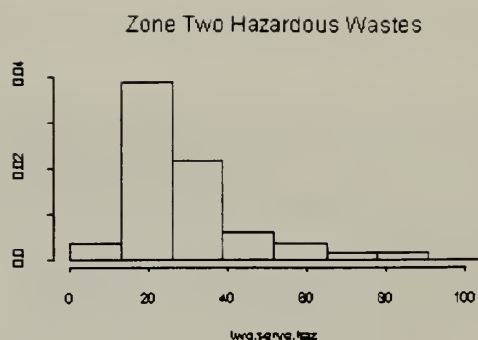
We also note that there are significant quantities of state and federally regulated waste in this zone, which may have different service times from other hazardous wastes. It should therefore be determined whether all wastes can be modeled with a single service time distribution or if separate models should be used for the three waste classes. The results of this analysis will be provided once and assumed hereafter.

All the small waste containers together:

Zone 2 Small Container Service Times with 13+Exp(16) Overlay



Splitting the wastes into waste classes:



Looking at the histograms, there does appear to be a difference in service times, so ANOVA testing can be used to determine if the difference is statistically significant, testing the hypothesis that mean service times for the waste classes are equal.

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Non-Reg	749	21584.81	28.81817	247.2682
Fed	59	2140	36.27119	563.27
State	67	1786.35	26.66194	253.5084

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	3489.171	2	1744.586	6.491264	0.001591	3.006051
Within Groups	234357.8	872	268.759			
Total	237847	874				

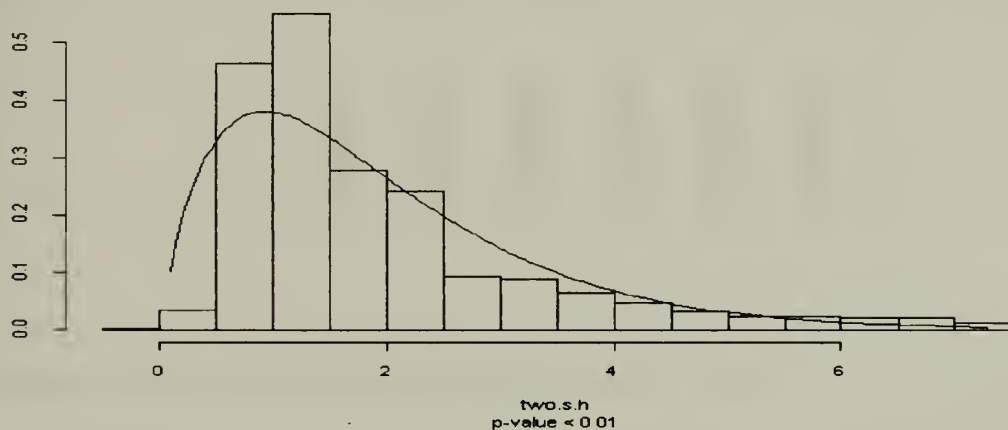
Analysis of Variance shows that we cannot accept the hypothesis that the mean amount of time it takes to process a state or federally regulated waste class is the same as

the amount of time it takes to process a hazardous only waste container (the p-value = 0.001591).

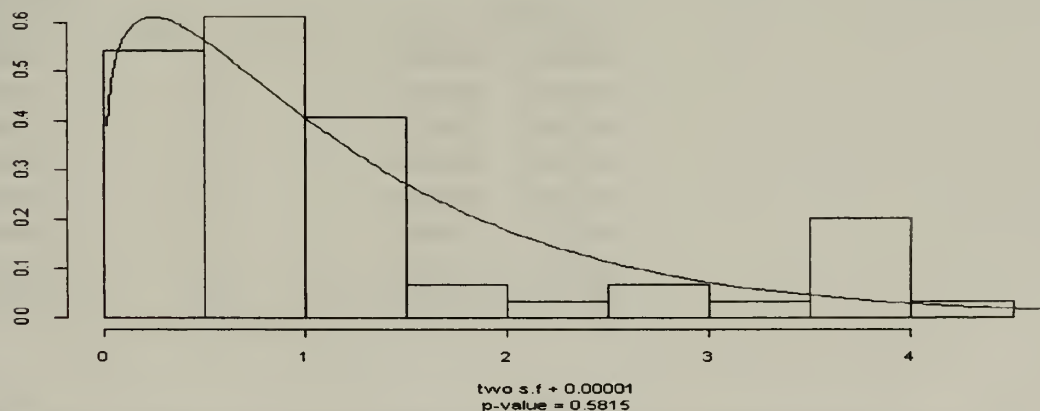
The arrival process for this zone will therefore need to separate the wastes in some manner so that different waste classifications can undergo different service times. It must also be noted that although most mixed wastes will be transferred to an on-site long term storage or treatment facility, rather than be manifested to off-site disposal facility directly from the WAA, the model only considers that the waste is no longer in the WAA, whether it goes to an on-site TSDF or off-site.

We therefore model each waste class service time separately. This is shown below:

Zone 2 Small HazWaste Weekly Disposals w/ 7+Gamma(11.3, 1.9) Overlay

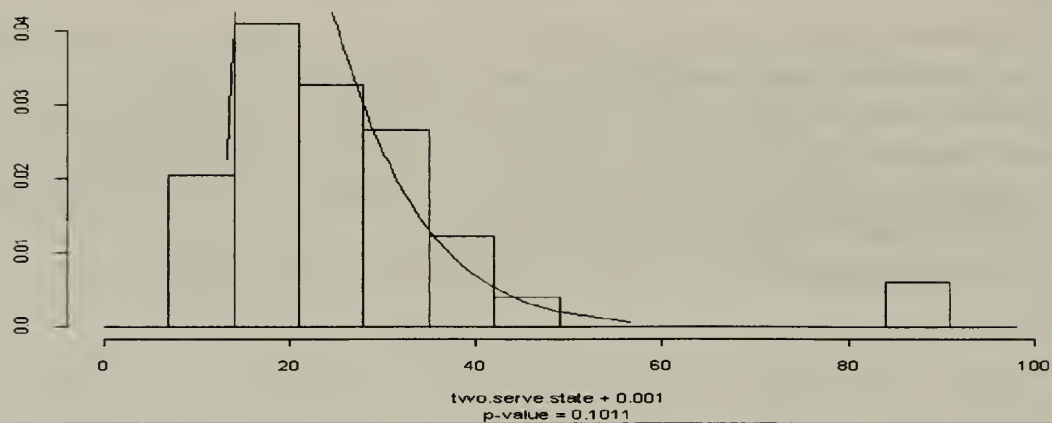


Zone 2 Small Fed. Reg. Waste Disposals w/ 10+Gamma(21 0.1.25) Overlay



As mentioned in Chapter 3, the “shift” is estimated as the lowest value of the data.

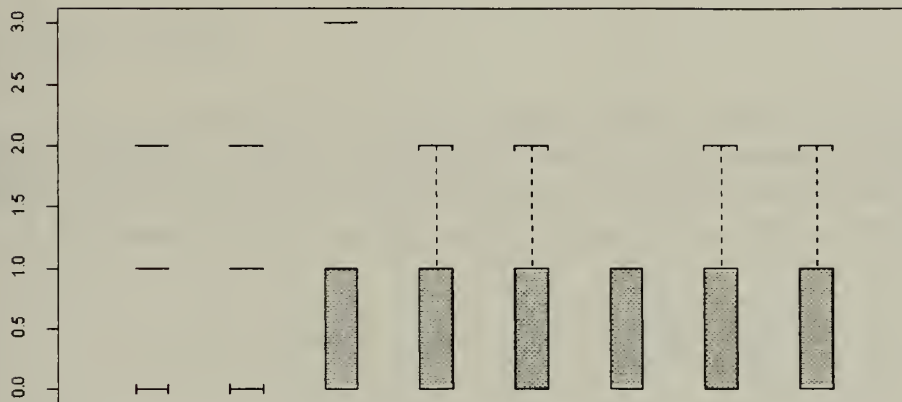
Zone 2 Small State Reg Wastes w/ 13+Gamma(6.405582,1.69017) Overlay



B. Large Containers.

Arrivals per week:

Boxplots for Large Drums Weekly Disposals in Zone Two



Performing ANOVA to test the hypothesis that $m_1 = m_2 = \dots = m_8$:

Anova: Single Factor

SUMMARY

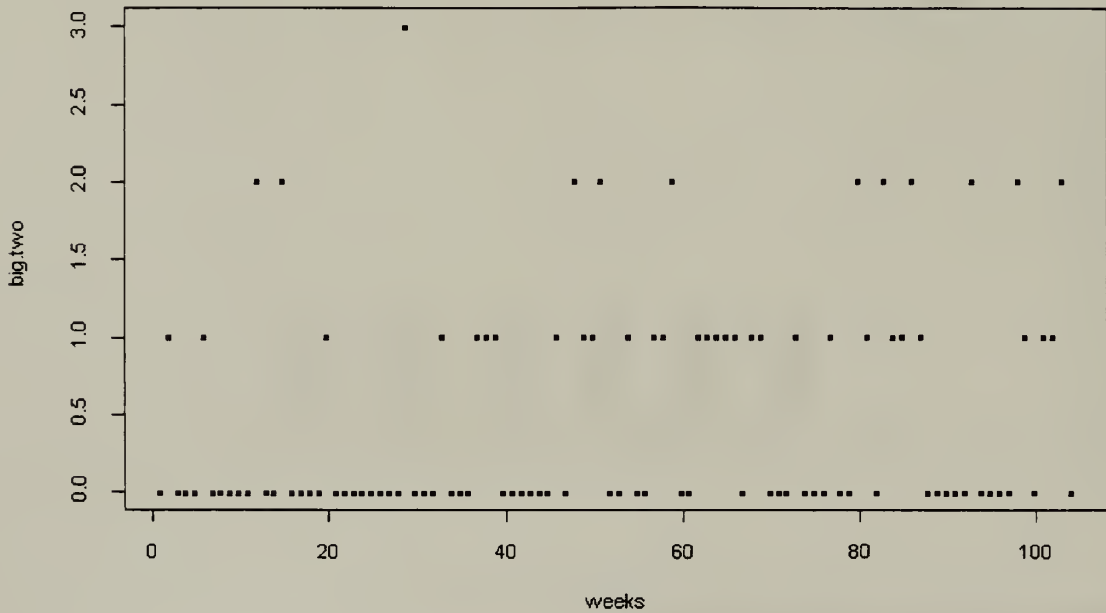
Groups	Count	Sum	Average	Variance
Column 1	13	4	0.307692	0.397436
Column 2	13	3	0.230769	0.358974
Column 3	13	7	0.538462	0.769231
Column 4	13	7	0.538462	0.602564
Column 5	13	9	0.692308	0.397436
Column 6	13	5	0.384615	0.25641
Column 7	13	10	0.769231	0.692308
Column 8	13	9	0.692308	0.730769

ANOVA

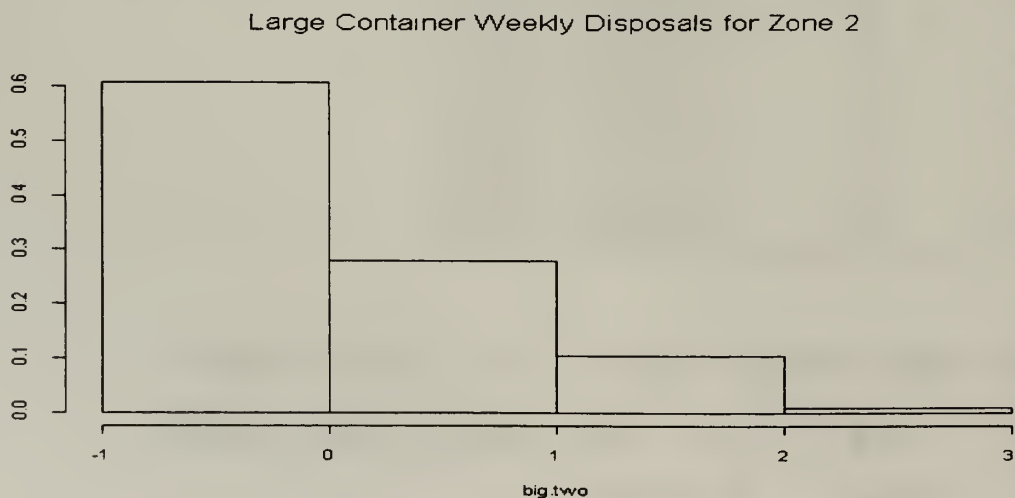
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	3.5	7	0.5	0.95122	0.471328	2.106468
Within Groups	50.46154	96	0.525641			
Total	53.96154	103				

The $p\text{-value} > 0.05$ indicates that we cannot reject the hypothesis that the mean number of containers being disposed each week is the same from one quarter to the next.

Now, let's plot the arrivals:



Linear regression won't reveal much with only three likely outcomes each week (0, 1, or 2 containers), and ANOVA already indicates no differences from one quarter to the next. Let's plot the histograms of weekly arrivals.



Rather than attempt to fit a common distribution to the arrival process for this waste, the empirical distribution derived from the data set will be used.

Empirical Distribution:

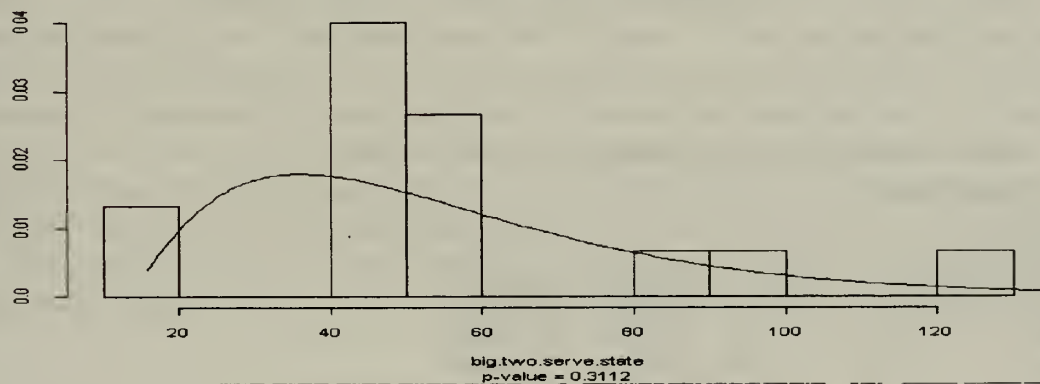
Arrivals	pmf	Arrivals	cmf
0	0.605769	0	0.605769
1	0.278846	1	0.884615
2	0.105769	2	0.990385
3	0.009615	3	1

Service Times:

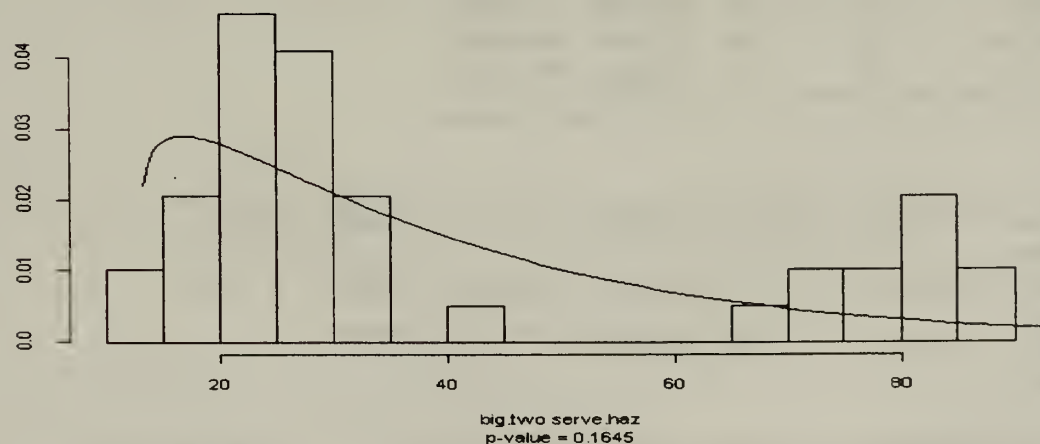
The service times for the large containers of state regulated and non-state regulated hazardous wastes also differ (there were no large containers of federally regulated wastes disposed from zone 2 during the period for which data was analyzed).

The results of approximating the distributions for the service times is shown below.

Zone 2 Large State Reg. Wastes w/ 13 + Gamma(18.81, 2.22) Overlay



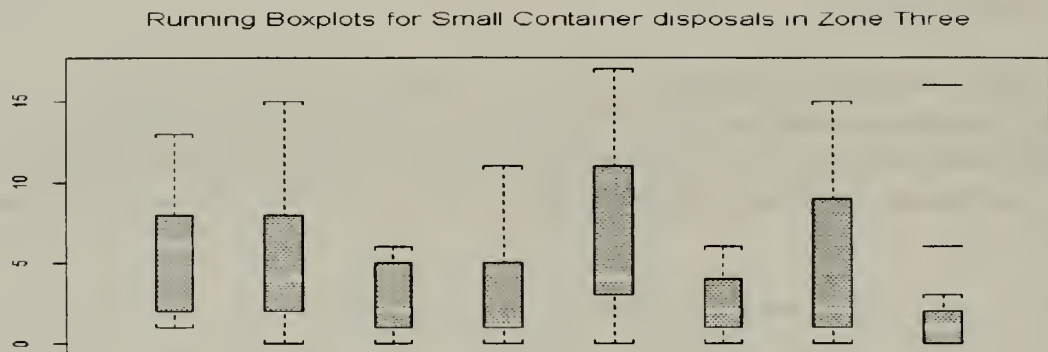
Zone Two Large Haz Waste Disposals w/13 + Gamma(23.65, 1.16) Overlay



3. Zone Three:

A. Small Containers.

Number of containers arriving per week:



ANOVA testing with hypothesis $\mu_1 = \mu_2 = \dots = \mu_8$:

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	70	5.384615	14.42308
Column 2	13	67	5.153846	20.30769
Column 3	13	35	2.692308	4.397436
Column 4	13	38	2.923077	10.07692
Column 5	13	86	6.615385	29.75641
Column 6	13	33	2.538462	3.435897
Column 7	13	59	4.538462	28.60256
Column 8	13	31	2.384615	19.58974

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	233.8365	7	33.40522	2.046422	0.056921	2.106468
Within Groups	1567.077	96	16.32372			
Total	1800.913	103				

With a p-value > 0.05 , we cannot reject the hypothesis that the mean number of small containers being disposed each week during the 8 quarters are equal.

Performing OLS regression yields the following results:

Residuals:

Min	1Q	Median	3Q	Max
-4.784	-3.028	-1.49	1.466	13.08

Coefficients:

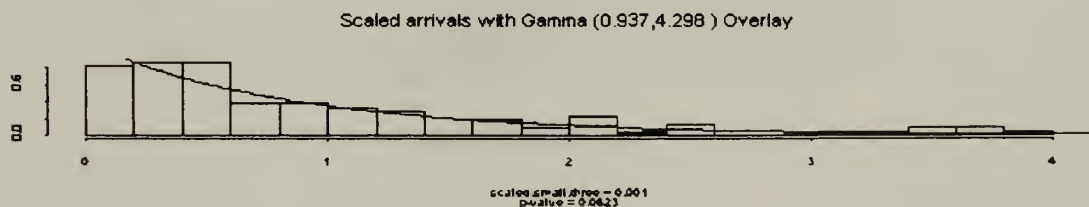
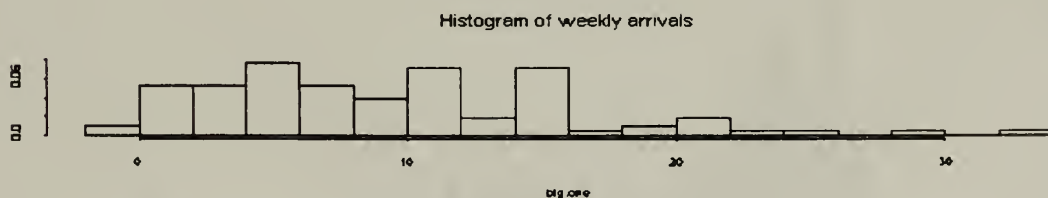
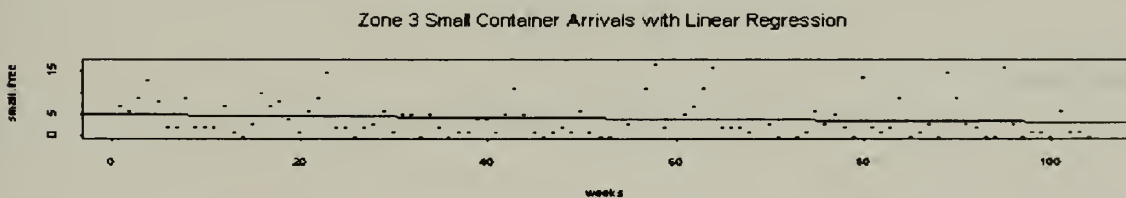
	Value	Std. Error
(Intercept)	5.0592	0.8217
weeks	-0.0196	0.0136

Again, the large standard error for the slope indicates that there is no strong evidence that the slope is significantly different from zero.

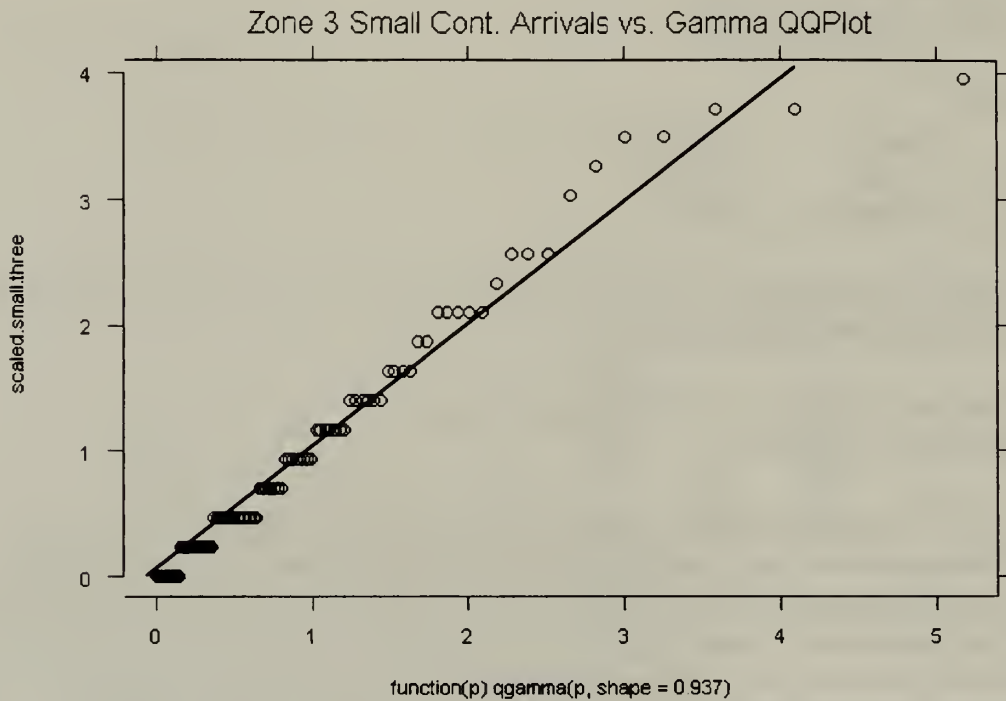
Residual standard error: 4.16 on 102 degrees of freedom

Multiple R-Squared: 0.02005

Slope = -0.0196, indicating an annual decrease of approximately 19% in the number of containers being disposed each week over the 104 weeks. However, the large standard error of the slope estimate ANOVA indicates indicate that we should be wary of assuming a decrease in the amount of waste generated. Comparing the mean number of containers being disposed from one year to the next directly indicates that a decrease in waste containers being disposed of just under 1% was realized each year during this period. We will model the number of arrivals as independent, identically distributed random variables. The histogram of the values is displayed below. A gamma distribution was found to summarize the data.



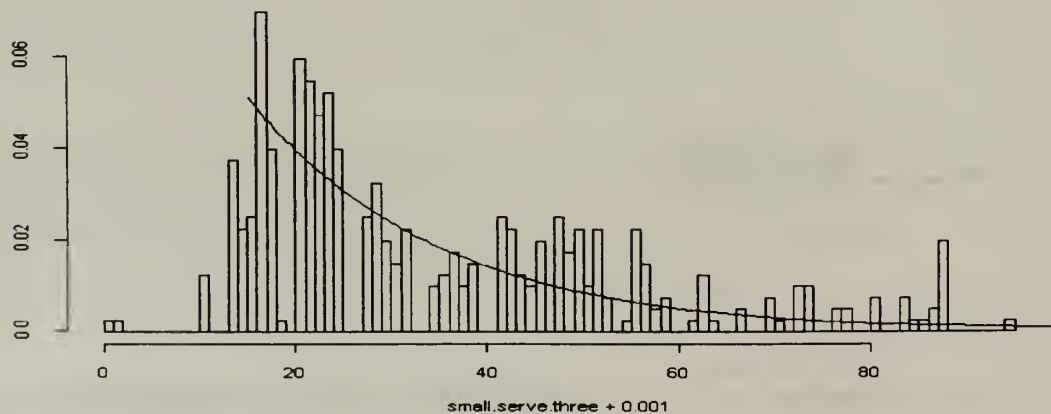
The Quantile-Quantile plot again gives a graphical representation of how closely the empirical distribution is approximated by the chosen Gamma distribution.



The QQPlot shows that the quantiles of the empirical distribution (the data values) closely follows the quantiles of the hypothetical gamma distribution that is being used to model the arrivals, and therefore graphically demonstrates what the high p-value for goodness of fit tells us; the hypothetical distribution does describe the data well.

Service Times:

Zone 3 Small Container Service Times w/ 15+Exp(19.6) Overlay

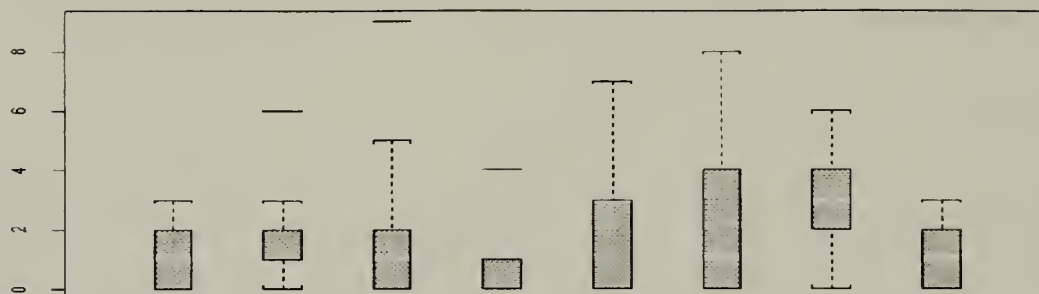


The shifted exponential distribution was the best summary (the common distribution resulting in the minimum residual error) for service times, but with a KS goodness of fit p -value < 0.01 . It must be used as the distribution of service time in the simulation model, since an empirical distribution of service times is impractical for use in the simulation model. Since only the average time will be used in the mathematical model, the poor fit of the distribution will have no effect on calculating the long-run average storage requirements.

B. Large Containers.

Number of arrivals per week:

Running Boxplots for Large Container Disposals in Zone Three



ANOVA testing for the hypothesis that $\mu_1 = \mu_2 = \dots = \mu_8$.

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	15	1.153846	0.974359
Column 2	13	19	1.461538	2.602564
Column 3	13	22	1.692308	7.064103
Column 4	13	9	0.692308	1.230769
Column 5	13	29	2.230769	5.525641
Column 6	13	27	2.076923	7.410256
Column 7	13	36	2.769231	3.358974
Column 8	13	12	0.923077	1.076923

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	45.45192	7	6.493132	1.776289	0.100846	2.106468
Within Groups	350.9231	96	3.655449			
Total	396.375	103				

The p-value > 0.05 shows that the null hypothesis should not be rejected.

The graphical trend line resulting from performing OLS Regression of the large container arrivals for this zone is shown below. With the data only taking on a small range of values close to zero, however, the usefulness of this information is suspect. The positively sloped trend line indicated that a greater number of large containers is being

disposed as time progresses and may indicate an area that needs to be examined for possible increasing storage capacity demand. The increase is less than 0.5 containers per week over the course of a year and would probably not cause any significant disruptions in the near future. Further, the relatively large standard error of the slope indicates that the slope is not significantly different than zero.

Performing the OLS regression yields:

Residuals:

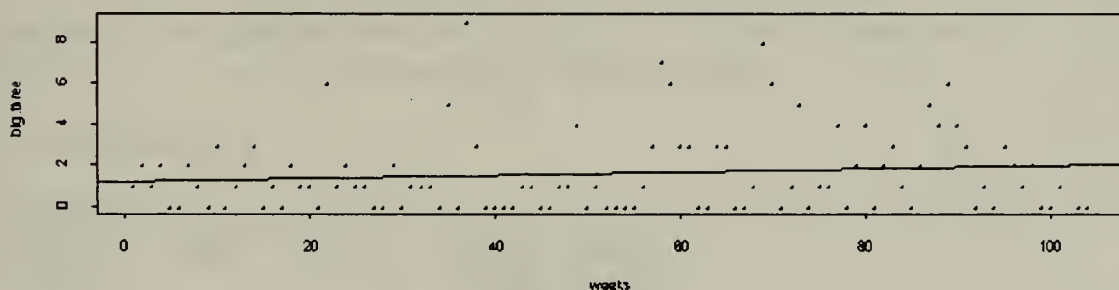
Min	1Q	Median	3Q	Max
-2.047	-1.496	-0.5063	0.8481	7.502

Coefficients:

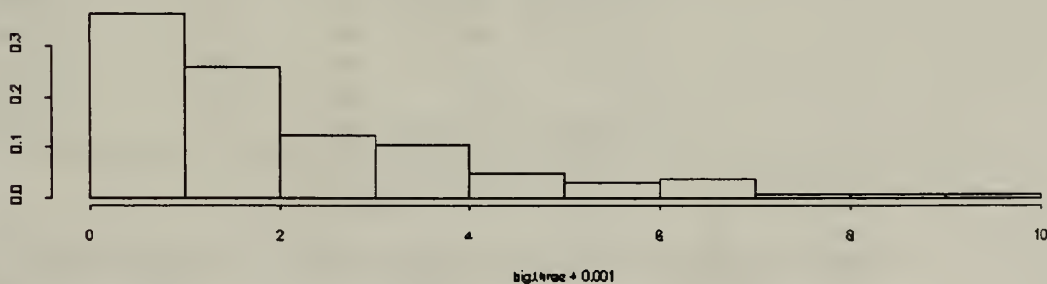
	Value	Std. Error
(Intercept)	1.1951	0.3863
weeks	0.0082	0.0064

We therefore model arrivals as independent, identically distributed random variables from the distribution described below.

Zone Three Large Container Arrivals with Linear Regression



Histogram of weekly arrivals

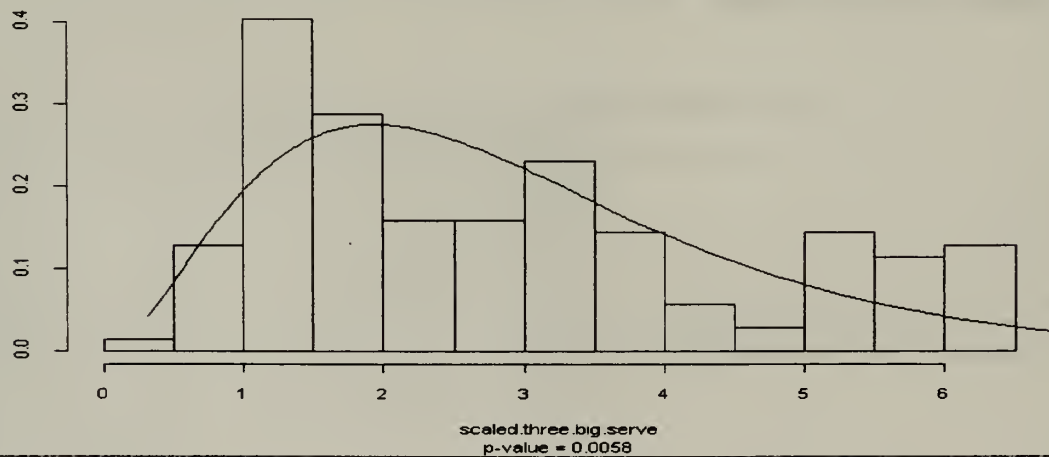


The arrival process resulted in only a small number of possible values, and will therefore be modeled using an empirical distribution.

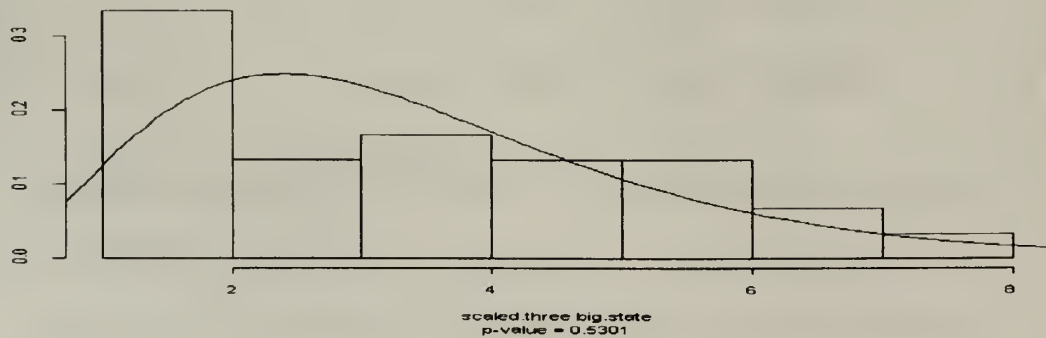
Arrivals	pmf	Arrivals	cmf
0	0.365385	0	0.365385
1	0.259615	1	0.625
2	0.125	2	0.75
3	0.105769	3	0.855769
4	0.048077	4	0.903846
5	0.028846	5	0.932692
6	0.038462	6	0.971154
7	0.009615	7	0.980769
8	0.009615	8	0.990385
9	0.009615	9	1

Service Times:

Zone Three Large Haz. Waste Cont. w/Gamma (14.08, 2.93) Overlay



Zone Three State Regulated Waste Service Time w/ Gamma Overlay

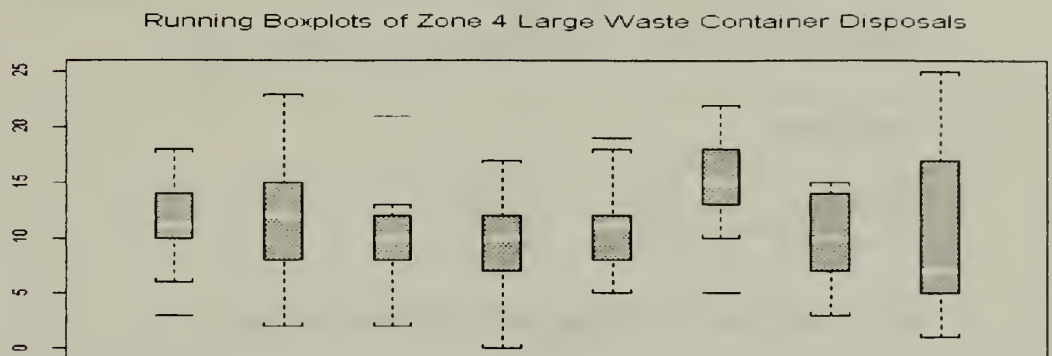


Shape = 3.394; Scale = 14.034.

4. Zone Four.

A. Large Containers.

Number of arrivals per week:



ANOVA testing indicates that the mean number of containers arriving for disposal each week is not changing significantly over time. With the null hypothesis of $\mu_1 = \mu_2 = \dots = \mu_8$, we obtain the resulting p-value = 0.188768.

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	148	11.38462	17.08974
Column 2	13	162	12.46154	49.76923
Column 3	13	127	9.769231	22.69231
Column 4	13	129	9.923077	18.91026
Column 5	13	144	11.07692	21.91026
Column 6	13	195	15	19.5
Column 7	13	130	10	13
Column 8	13	136	10.46154	57.26923

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	282.2981	7	40.3283	1.465544	0.188768	2.106468
Within Groups	2641.692	96	27.51763			
Total	2923.99	103				

There is, therefore, insufficient evidence to suggest that the number of containers arriving each week is changing from one quarter to the next.

Performing OLS regression yields the following results:

Residuals:

Min	1Q	Median	3Q	Max
-11.26	-4.124	-0.187	2.869	13.88

Coefficients:

	Value	Std. Error
(Intercept)	11.4330	1.0575
weeks	-0.0033	0.0175

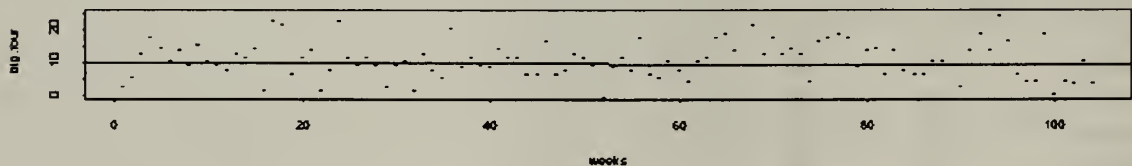
Again, the slope is not significantly different from zero.

Residual standard error: 5.353 on 102 degrees of freedom

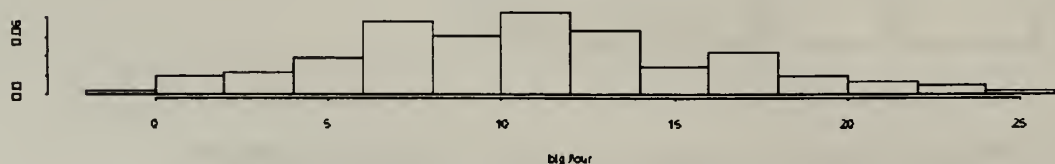
Multiple R-Squared: 0.0003495

Slope = -0.0033, indicating a decrease in the number of containers being disposed each week of approximately 1.5% per year. With the slope being not significantly different from zero, however, there may be no noticeable decrease at all.

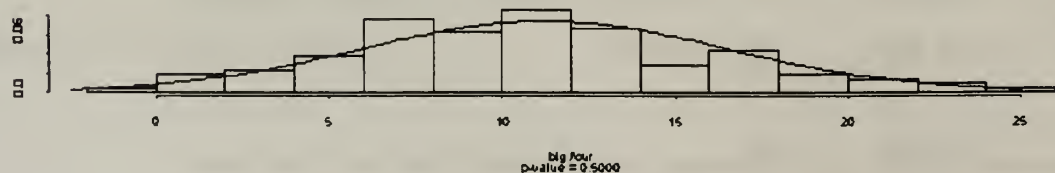
Zone Four Large Container Arrivals with Linear Regression



Histogram of weekly arrivals



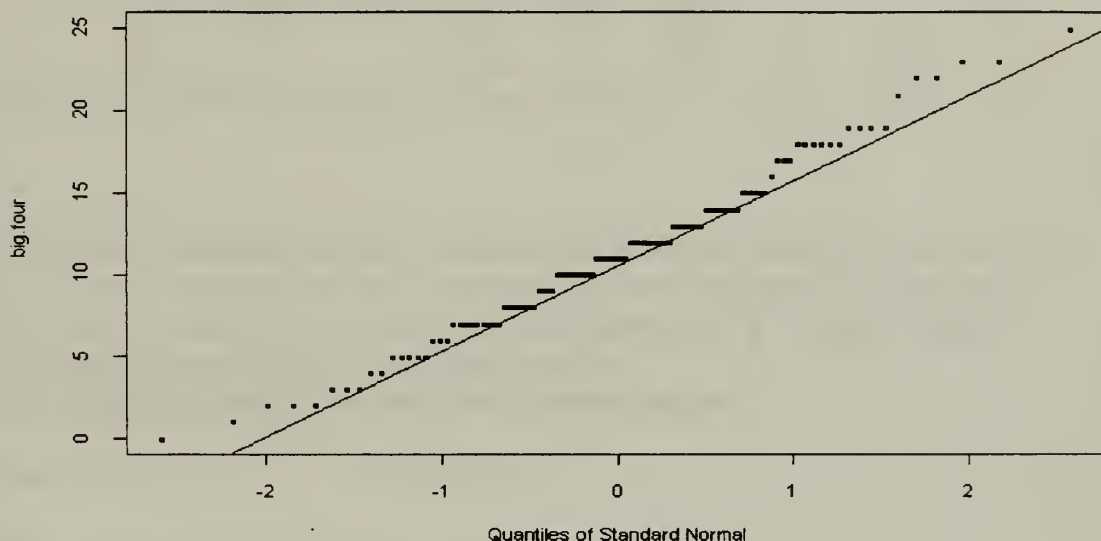
Arrivals with Normal (11.26,5.33) Overlay



The best summary distribution to model the number of containers arriving each week is the normal distribution. The KS Goodness of fit test performed in S-Plus yields a p-value greater than 0.10 (actually 0.225), and therefore reverts to performing a Dallal-Wilkinson approximation to calculate the p-value in testing composite normality. This test yields a resulting p-value = 0.500 when comparing the distribution of the data to the normal distribution with the same mean and variance.

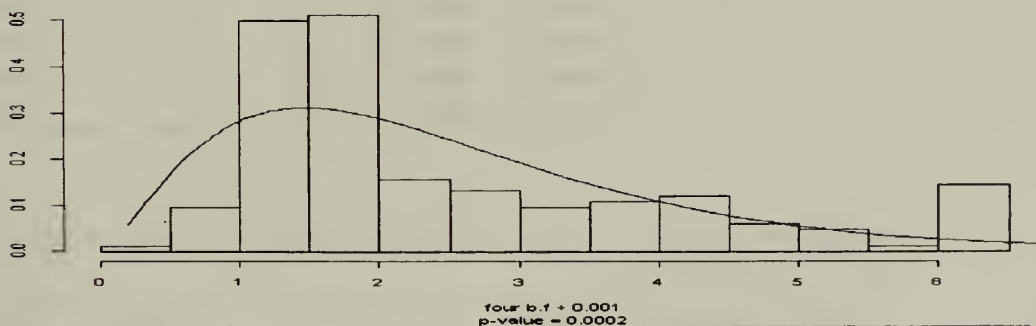
The QQ Plot shows the relationship of the empirical distribution quantiles to the quantiles of the hypothetical normal distribution with the same parameters.

Zone 4 Large Container Arrivals vs. $N(11.26, 5.33)$ QQPlot

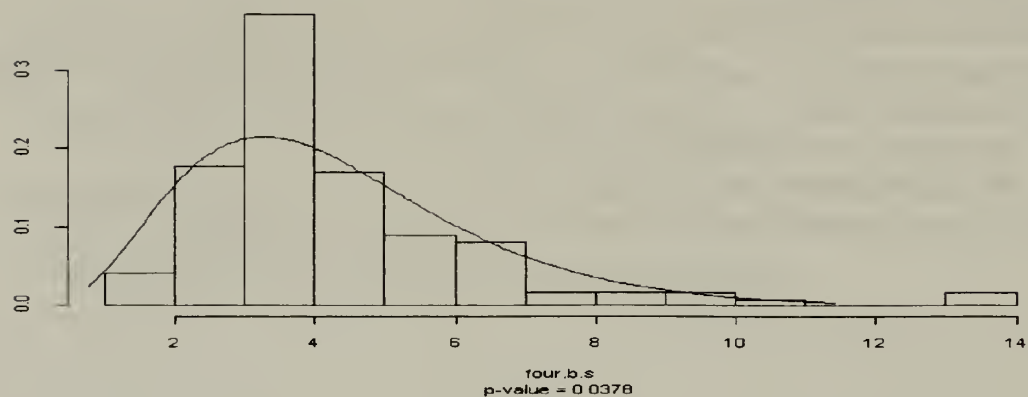


Service Times:

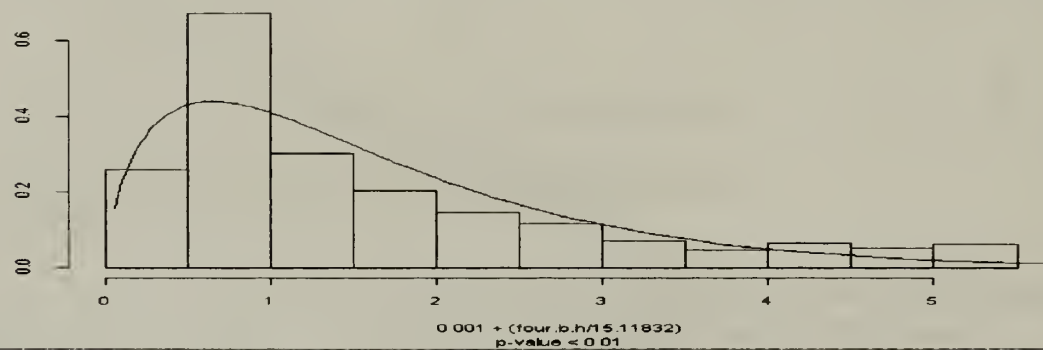
Zone 4 Large Fed. Regulated Waste Service Times w/Gamma Overlay



Zone 4 Large State Reg Waste Cont. Disposals w/ Gamma Overlay

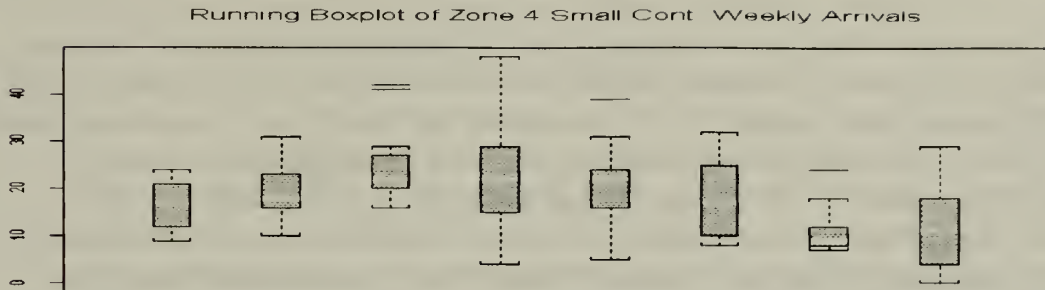


Zone 4 Large Haz Wastes Container Disposals w/Gamma(15 11,1 65)



B. Small Containers.

Number of container arrivals per week:



Observing the running boxplots, we get an impression of what the ANOVA testing will show. Namely, while the first four quarters seem to have approximately the same mean value, the downward trend of containers being disposed in the last four quarters clearly indicates that not all of the mean values are equal.

Performing the ANOVA test yields the following results:

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	13	216	16.61538	27.25641
Column 2	13	263	20.23077	43.19231
Column 3	13	324	24.92308	66.57692
Column 4	13	294	22.61538	142.9231
Column 5	13	272	20.92308	93.74359
Column 6	13	244	18.76923	73.35897
Column 7	13	150	11.53846	24.4359
Column 8	13	157	12.07692	88.91026

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	2085.077	7	297.8681	4.252241	0.000396	2.106468
Within Groups	6724.769	96	70.04968			
Total	8809.846	103				

With a p-value < 0.05 , we reject the hypothesis that the mean number of containers arriving each week has remained the same over the two year period, as suspected.

Noting this, there was still no seasonality detected in the model (the resulting residuals of the detrended data exhibited no clear seasonal influence). It is suspected that this zone in particular achieved success in decreasing the volume of waste being generated during 1996 (perhaps by design or perhaps as a result of decreasing research activity), which has a direct affect on the number of small containers being disposed. Since no seasonality was present, it appears that the downward trend is having significant effect on weekly waste arrivals, causing ANOVA to indicate we should reject the null hypothesis. Using the fact that quantities are decreasing can aid in determining exact storage requirements. Since it is the primary goal of this thesis to determine if there will be enough waste storage space available, we can take a pessimistic view of the trend and assume that the overall waste disposal process for the entire period can be used to determine demand for space.

If this quantity alone is a deciding factor on whether the re-engineering process can go forward, further modeling of the waste arrivals would have to be performed.

It must be noted that this is the only zone and waste container size for which the waste reduction was significant enough to reject the hypothesis that the mean number of containers was equal over disjoint time periods using Analysis of Variance.

Performing OLS regression for the last 6 quarters yielded the following results:

Residuals:

Min	1Q	Median	3Q	Max
-17.42	-6.647	-1.692	5	24.62

Coefficients:

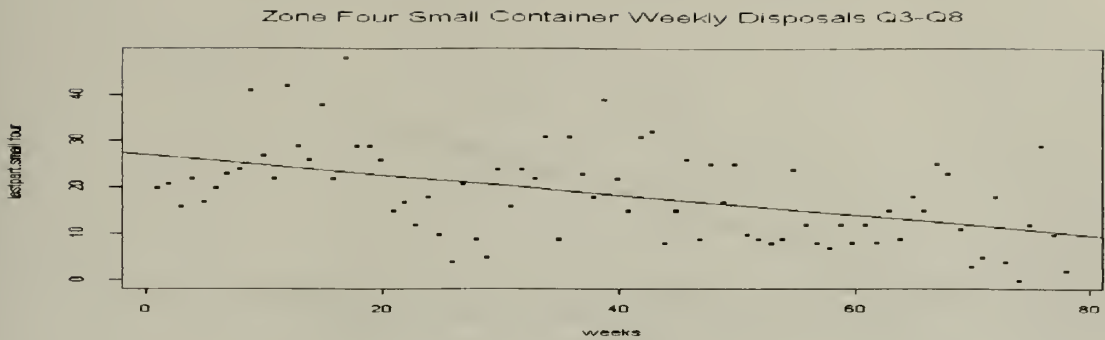
	Value	Std. Error
(Intercept)	27.0842	2.0318
weeks	-0.2180	0.0447

Residual standard error: 8.886 on 76 degrees of freedom

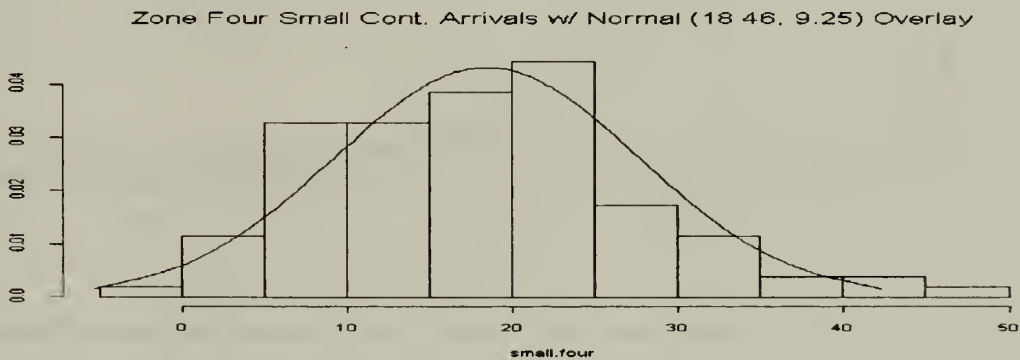
Multiple R-Squared: 0.2384

With a Multiple R-Squared value of 0.2384, we can also conclude that there is a direct correlation between time and the lesser quantities of waste being generated, again indicating that the trend is clear in this zone.

Slope = -0.2180, indicating an annual decrease of nearly 42% in the number of containers being disposed each week. Looking back at the ANOVA table, this estimate seems valid, reflecting the decrease from an average of 24 containers per week in the third quarter of 1995 to only 11 containers per week in the last quarter of 1996. There also appears to be a seasonal or cyclic component affecting the first year of the data, but the effect is much less pronounced in the more recent data. Since the trend is not clear over the entire period of the data, these affects will not be analyzed.

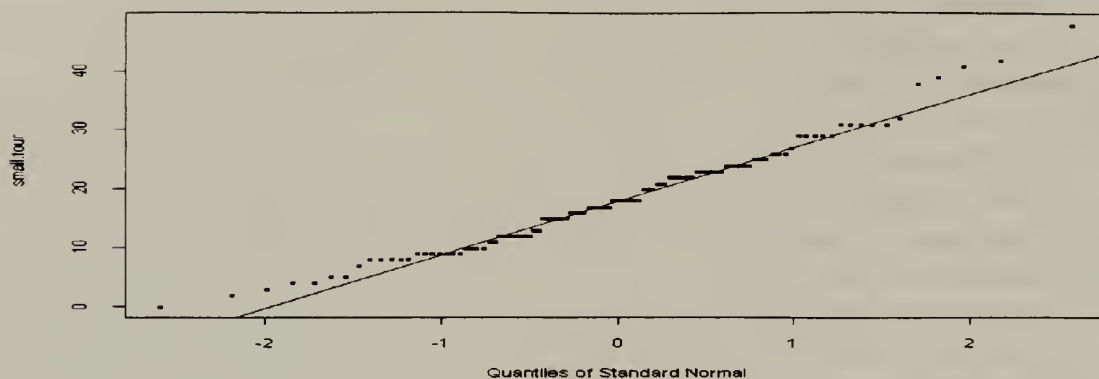


Using all of the data to model arrivals will give us a “pessimistic” estimate for arrivals, and will be used to model arrivals. Thus, the number of arrivals per week will be modeled as independent, identically distributed random variables. Plotting a histogram to determine the relative frequency of the number of containers being disposed each week revealed a mass with a central peak, indicating that a normal distribution may be the best fitting distribution. Performing the KS goodness of fit test performed in S-Plus (again referring to the Dallal-Wilkinson approximation, as noted for Zone 4 large containers) yielded a $p\text{-value} = 0.500$ when testing for composite normality. The histogram with an overlay of the estimated normal distribution is shown below.



The linearity of the QQ plot of the quantiles of the empirical distribution vs. the quantiles of the hypothetical best-fitting normal distribution also indicate that a normal distribution is a good model for the arrival data.

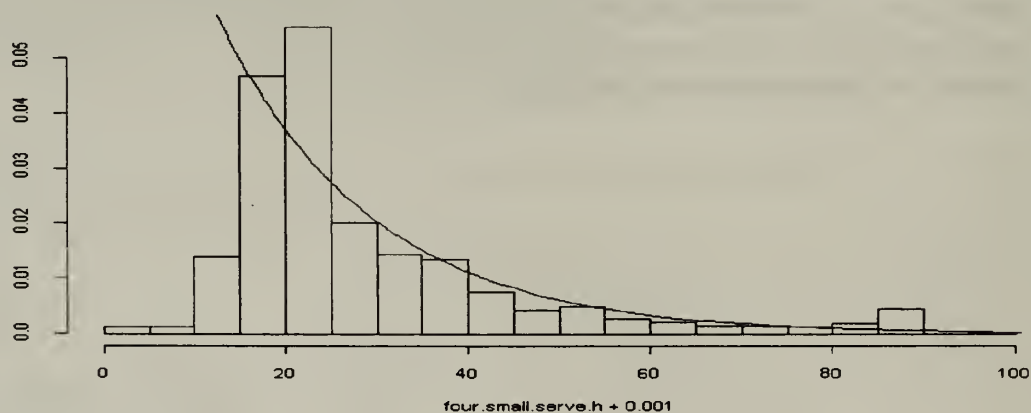
Zone Four Small Container Arrivals vs N(18.46, 9.25) QQPlot



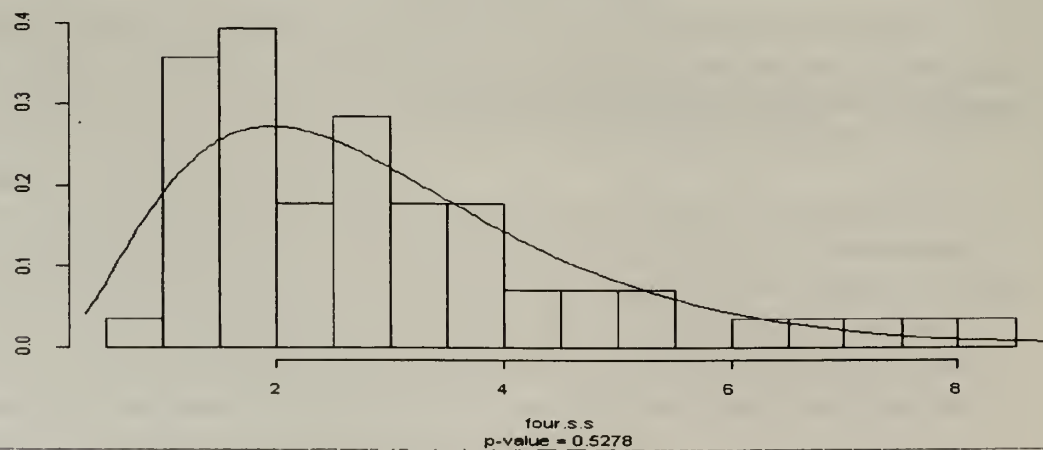
Service Times:

Analyzing the service times for wastes in zone four again indicated a need to model waste classes separately with the following results:

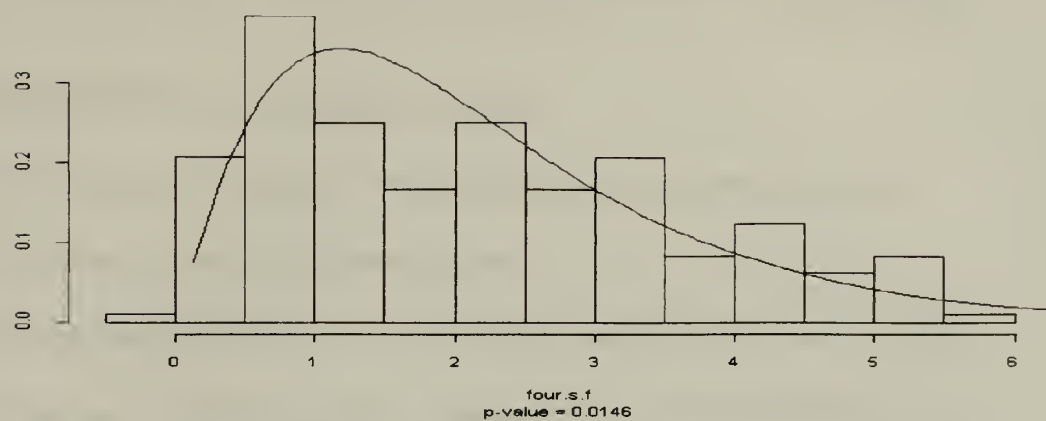
Zone 4 Small Hazardous Waste Service Times w/12+Exp(16.75)



Zone 4 Small State Reg. Waste Cont. Disposals w/Gamma Overlay



Zone 4 Small Fed. Regulated Waste Cont. Disposals w/Gamma Overlay



APPENDIX B : RESULTS OF MATHEMATICAL MODEL

A. DESCRIPTION OF VARIOUS SYSTEMS

The following tables denote the results of applying the mathematical model described in Chapter IV under various assumptions.

The initial model demonstrates the results of the model applied under the “old” system, or status quo. Under this system, containers are shipped from the WAA on a weekly basis, giving us 7 days as the “Time between shipments.” The average number of containers arriving each week is computed from the historical data. The average service time for wastes in each region is then also computed from the historical data. The average weekly demand for storage space is then calculated in units of 5 CGEs., and is equal to weekly arrival rate times the service time (in weeks). Compatibility of wastes in storage is not addressed in this model. (TABLE B-1)

The model labeled “New system - 0% WEF” is derived by using the incoming numbers of containers from various waste streams and their service times under the “old” system, and assigning additional duties (and therefore service time) for the hazardous waste processing in the WAA. None of the waste entering the WAA is considered to be pre-evaluated on a Waste Evaluation Form (WEF). Specifically, it is now assumed that random chemical analysis of 10% of the wastes will occur in the WAA, and that analyzing a container of waste takes an average of 14 days to perform. [Gagner] Additionally, since wastes will now be shipped directly off-site from the WAA, the time required to manifest a waste container to an outgoing shipment will now occur in the WAA. This process is usually performed the week prior to the shipment going out, and is therefore assumed to

take a deterministic amount of time equal to 7 days. [Various LLNL shipping personnel] It was also noted that wastes could be shipped within 48 hours of receiving notification that classification of the waste was complete, but this process is not typical and incurs extra costs. Expedited shipping will therefore not be considered in the model. Shipments then depart approximately twice a week, or one shipment every 3.5 days on the average. [Cadwell] This represents the worst case scenario for storage requirements, when no early identification and classification of wastes is performed. (TABLE B-2)

The model labeled "New System - 25% WEF" is derived using the above estimates for time, but it is also assumed that approximately 75% of hazardous waste will undergo traditional WAA service with the remaining 25% arriving at the WAA already classified by a WEF and containerized for shipment in DOT approved containers. Those wastes that are classified by a WEF prior to arrival must still wait for manifesting for shipment (7 days), and 10% will undergo random chemical analysis (14 days). The amount of time required to perform traditional WAA technician service on State and Federally regulated wastes will not change appreciably under the re-engineered process [Caldwell]. (TABLE B-3)

The model labeled "New System - 50% WEF" is derived using the above information, but with the assumption that 50% of incoming hazardous waste is classified by WEF. Currently, it is estimated that 50% of the material arriving at the WAA is classified on a WEF, so this result is based on the best estimate (most likely scenario) of what the re-engineering will accomplish. [Fischer] (TABLE B-4)

The model labeled "New System -75% WEF" is also derived using the above information, but with the assumption that 75% of incoming hazardous waste is classified

by WEF. It is possible that this may be attained in the future, but unlikely that 100% of incoming materials will ever be able to be classified on WEFs, and is therefore considered to approach the best case scenario for the re-engineering. (TABLE B-5)

The results of this analysis is provided has been provided in Chapter IV.

"Old" System

Zone	Cont. Size & (waste class)	% of Arrivals by Class	Average Number of Containers arriving per week	Mean 5 GCE Arrival rate	Mean WAA Service time in days.	Time Between Shipments(days)	Average Weekly Demand for Storage Space	Average Age at Shipping(days)
1	Small	100	4.53	4.53	32.10	7.00	23.04	35.60
1	Large	100	9.73	<u>29.19</u>	26.60	7.00	<u>125.52</u>	<u>30.10</u>
1	TOTAL			33.72			148.56	31.85
2	Small (H)	85	6.87	5.84	28.80	7.00	26.95	32.30
2	Small (S)	8	6.87	0.55	26.62	7.00	2.36	30.12
2	Small (F)	7	6.87	0.48	36.27	7.00	2.73	39.77
2	Large (H)	72	0.52	1.12	40.41	7.00	7.05	43.91
2	Large (S)	28	0.52	<u>0.44</u>	54.80	7.00	<u>3.64</u>	<u>58.30</u>
2	TOTAL			8.43			42.73	33.72
3	Small	100	4.03	4.03	34.43	7.00	21.84	37.93
3	Large (H)	83	1.65	4.11	41.32	7.00	26.31	44.82
3	Large (S)	17	1.65	<u>0.84</u>	47.63	7.00	<u>6.15</u>	<u>51.13</u>
3	TOTAL			8.98			54.29	40.24
4	Small (H)	87	18.69	16.26	28.27	7.00	73.80	31.77
4	Small (S)	3	18.69	0.56	32.80	7.00	2.91	36.3
4	Small (F)	10	18.69	1.87	40.10	7.00	11.64	43.6
4	Large (H)	75	11.26	25.34	33.62	7.00	134.35	37.12
4	Large (S)	11	11.26	3.72	27.66	7.00	16.54	31.16
4	Large (F)	14	11.26	<u>4.73</u>	33.83	7.00	<u>25.22</u>	<u>37.33</u>
4	TOTAL			52.47			264.46	34.37

Zone	Cont. Size & (waste class)	% of Arrivals by Class	Average Number of Containers arriving per week	Mean 5 GCE Arrival rate	Mean WAA Service time in days.	Time Between Shipments(days)	Average Weekly Demand for Storage Space	Average Age at Shipping(days)
1	Small	100	4.53	4.53	40.50	3.50	27.34	42.25
1	Large	100	9.73	<u>29.19</u>	35.00	3.50	<u>153.25</u>	<u>36.75</u>
1	TOTAL			33.72			180.59	38.50
2	Small (H)	85	6.87	5.84	37.20	3.50	32.49	38.95
2	Small (S)	8	6.87	0.55	26.62	3.50	2.23	28.37
2	Small (F)	7	6.87	0.48	36.27	3.50	2.61	38.02
2	Large (H)	72	0.52	1.12	48.81	3.50	8.11	50.56
2	Large (S)	28	0.52	<u>0.44</u>	54.80	3.50	<u>3.53</u>	<u>56.55</u>
2	TOTAL			8.43			48.97	39.04
3	Small	100	4.03	4.03	42.83	3.50	25.67	44.58
3	Large (H)	83	1.65	4.11	49.72	3.50	30.21	51.47
3	Large (S)	17	1.65	<u>0.84</u>	47.63	3.50	<u>5.94</u>	<u>49.38</u>
3	TOTAL			8.98			61.81	46.48
4	Small (H)	87	18.69	16.26	36.67	3.50	89.25	38.42
4	Small (S)	3	18.69	0.56	32.80	3.50	2.77	34.55
4	Small (F)	10	18.69	1.87	40.10	3.50	11.17	41.85
4	Large (H)	75	11.26	25.34	42.02	3.50	158.42	43.77
4	Large (S)	11	11.26	3.72	27.66	3.50	15.61	29.41
4	Large (F)	14	11.26	<u>4.73</u>	33.83	3.50	<u>24.04</u>	<u>35.58</u>
4	TOTAL			52.47			301.25	39.55

TABLE B-2

New System - 25% WEF

Zone	Cont. Size & (waste class)	% of Arrivals by Class	Average Number of Containers arriving per week	Mean 5 GCE Arrival rate	Mean WAA Service time in days.	Time Between Shipments(days)	Average Weekly Demand for Storage Space	Average Age at Shipping(days)
1	Small	100	4.53	4.53	32.48	3.50	22.15	34.23
1	Large	100	9.73	<u>29.19</u>	28.35	3.50	<u>125.52</u>	<u>30.10</u>
1	TOTAL			33.72			147.67	31.41
2	Small (H)	85	6.87	5.84	30.00	3.50	26.49	31.75
2	Small (S)	8	6.87	0.55	26.62	3.50	2.23	28.37
2	Small (F)	7	6.87	0.48	36.27	3.50	2.61	38.02
2	Large (H)	72	0.52	1.12	38.71	3.50	6.49	40.46
2	Large (S)	28	0.52	<u>0.44</u>	54.80	3.50	<u>3.53</u>	<u>56.55</u>
2	TOTAL			8.43			41.35	32.84
3	Small	100	4.03	4.03	34.22	3.50	20.71	35.9725
3	Large (H)	83	1.65	4.11	39.39	3.50	24.15	41.14
3	Large (S)	17	1.65	<u>0.84</u>	47.63	3.50	<u>5.94</u>	<u>49.38</u>
3	TOTAL			8.98			50.79	37.88
4	Small (H)	87	18.69	16.26	29.60	3.50	72.83	31.3525
4	Small (S)	3	18.69	0.56	32.80	3.50	2.77	34.55
4	Small (F)	10	18.69	1.87	40.10	3.50	11.17	41.85
4	Large (H)	75	11.26	25.34	33.62	3.50	128.00	35.365
4	Large (S)	11	11.26	3.72	27.66	3.50	15.61	29.41
4	Large (F)	14	11.26	<u>4.73</u>	33.83	3.50	<u>24.04</u>	<u>35.58</u>
4	TOTAL			52.47			254.42	33.34

Zone	Cont. Size & (waste class)	% of Arrivals by Class	Average Number of Containers arriving per week	Mean 5 GCE Arrival rate	Mean WAA Service time in days.	Time Between Shipments(days)	Average Weekly Demand for Storage Space	Average Age at Shipping(days)
1	Small	100	4.53	4.53	24.45	3.50	16.96	26.20
1	Large	100	9.73	29.19	21.70	3.50	97.79	23.45
1	TOTAL			33.72			114.74	24.32
2	Small (H)	85	6.87	5.84	22.80	3.50	20.48	24.55
2	Small (S)	8	6.87	0.55	26.62	3.50	2.23	28.37
2	Small (F)	7	6.87	0.48	36.27	3.50	2.61	38.02
2	Large (H)	72	0.52	1.12	28.61	3.50	4.87	30.36
2	Large (S)	28	0.52	0.44	54.80	3.50	3.53	56.55
2	TOTAL			8.43			33.72	26.64
3	Small	100	4.03	4.03	25.62	3.50	15.75	27.365
3	Large (H)	83	1.65	4.11	29.06	3.50	18.08	30.81
3	Large (S)	17	1.65	0.84	47.63	3.50	5.94	49.38
3	TOTAL			8.98			39.77	29.28
4	Small (H)	87	18.69	16.26	22.54	3.50	56.41	24.285
4	Small (S)	3	18.69	0.56	32.80	3.50	2.77	34.55
4	Small (F)	10	18.69	1.87	40.10	3.50	11.17	41.85
4	Large (H)	75	11.26	25.34	25.21	3.50	97.58	26.96
4	Large (S)	11	11.26	3.72	27.66	3.50	15.61	29.41
4	Large (F)	14	11.26	4.73	33.83	3.50	24.04	35.58
4	TOTAL			52.47			207.58	27.13

TABLE B-4

New System - 75% WEF

Zone	Cont. Size & (waste class)	% of Arrivals by Class	Average Number of Containers arriving per week	Mean 5 GCE Arrival rate	Mean WAA Service time in days.	Time Between Shipments(days)	Average Weekly Demand for Storage Space	Average Age at Shipping(days)
1	Small	100	4.53	4.53	16.43	3.50	11.76	18.18
1	Large	100	9.73	<u>29.19</u>	15.05	3.50	<u>70.06</u>	<u>16.80</u>
1	TOTAL			33.72			81.82	17.24
2	Small (H)	85	6.87	5.84	15.60	3.50	14.47	17.35
2	Small (S)	8	6.87	0.55	26.62	3.50	2.23	28.37
2	Small (F)	7	6.87	0.48	36.27	3.50	2.61	38.02
2	Large (H)	72	0.52	1.12	18.50	3.50	3.25	20.25
2	Large (S)	28	0.52	<u>0.44</u>	54.80	3.50	<u>3.53</u>	<u>56.55</u>
2	TOTAL			8.43			26.09	20.43
3	Small	100	4.03	4.03	17.01	3.50	10.80	18.7575
3	Large (H)	83	1.65	4.11	18.73	3.50	12.02	20.48
3	Large (S)	17	1.65	<u>0.84</u>	47.63	3.50	<u>5.94</u>	<u>49.38</u>
3	TOTAL			8.98			28.76	20.69
4	Small (H)	87	18.69	16.26	15.47	3.50	39.99	17.2175
4	Small (S)	3	18.69	0.56	32.80	3.50	2.77	34.55
4	Small (F)	10	18.69	1.87	40.10	3.50	11.17	41.85
4	Large (H)	75	11.26	25.34	16.81	3.50	67.16	18.555
4	Large (S)	11	11.26	3.72	27.66	3.50	15.61	29.41
4	Large (F)	14	11.26	<u>4.73</u>	33.83	3.50	<u>24.04</u>	<u>35.58</u>
4	TOTAL			52.47			160.74	20.93

APPENDIX C : RESULTS OF THE SIMULATION MODEL

A. OVERVIEW OF SIMULATION RESULTS.

The waste management system was not simulated as a single process, but rather was split with separate simulations run for each "size" waste container (large or small) and each Zone (one through four). Statistics regarding the state of the system can be output to a file at user defined intervals. Since the data of interest were weekly peak inventory levels, the "virtual" inventory of the model was output to a file each week just after waste was generated into the system. Once a waste container was created, it was a separate entity in the model. This means that when 2 entities are created, each flows through the system separate from the other, taking on its own randomly distributed service times and probability of being denoted to the model as a state or federally regulated waste.

No attempt was made to identify wastes by hazard code (acidic, alkali, flammable, etc.) since analysis found incompatible wastes to make up a percentage of the total waste small enough that physical separation could be accomplished through use of other compatible waste containers. If further separation of the incompatible waste is needed, an additional percentage of empty storage space would have to be added.

Each simulation was run 10 times per Zone, per waste container size, per system considered, for a total of 400 runs. The mean values for the average number of containers in storage and average age of waste at time of shipment for each 10 run subset was computed and the results were then compared with the expected value derived using the mathematical model to ensure that the simulation was running properly. The stored peak

inventory data for large and small wastes for a given zone container size and policy were then recalled and the results analyzed and tabulated.

The long run average results from the runs for each zone will be shown first, with the expected values from the mathematical model and mean of the subset of simulation runs shown in bold. Following this will be the tabulated results for the peak inventory values for that zone.

Zone 1, Small Wastes, "Old" System.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	35.913	15.500	134.50	573
Off Site_Ta	35.530	15.500	134.50	599
Off Site_Ta	33.964	15.500	120.50	588
Off Site_Ta	35.285	15.500	120.50	582
Off Site_Ta	34.990	15.500	183.50	612
Off Site_Ta	36.614	15.500	141.50	731
Off Site_Ta	35.199	15.500	162.50	732
Off Site_Ta	36.180	15.500	162.50	700
Off Site_Ta	35.241	15.500	176.50	595
Off Site_Ta	36.478	15.500	148.50	642
Mean	35.54			
Standard Dev.	0.79			
Expected Value	35.60			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	20.525	6.0000	58.000	13.000
NSTO(WAA)	21.220	6.0000	58.000	15.000
NSTO(WAA)	20.032	6.0000	48.000	14.000
NSTO(WAA)	20.533	5.0000	63.000	20.000
NSTO(WAA)	21.483	3.0000	53.000	10.000
NSTO(WAA)	26.646	9.0000	61.000	15.000
NSTO(WAA)	25.865	7.0000	65.000	20.000
NSTO(WAA)	25.307	5.0000	67.000	27.000
NSTO(WAA)	21.375	5.0000	55.000	25.000
NSTO(WAA)	23.404	7.0000	56.000	20.000
Mean	22.64			
Standard Dev.	2.47			
Expected Value	23.04			

Zone 1, Large Wastes, "Old" System.

Results for 10 Runs, each 1500 time units (days) in length.

Data gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	29.739	15.500	141.50	1346
Off Site_Ta	29.395	15.500	127.50	1472
Off Site_Ta	29.322	15.500	134.50	1303
Off Site_Ta	29.677	15.500	169.50	1420
Off Site_Ta	29.901	15.500	141.50	1324
Off Site_Ta	29.282	15.500	162.50	1383
Off Site_Ta	29.337	15.500	141.50	1463
Off Site_Ta	29.881	15.500	141.50	1248
Off Site_Ta	30.086	15.500	148.50	1314
Off Site_Ta	29.101	15.500	134.50	1475
Mean	29.57			
Standard Dev.	0.33			
Expected Value	30.10			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	39.977	12.000	77.000	26.000
NSTO(WAA)	43.220	22.000	91.000	30.000
NSTO(WAA)	37.886	15.000	68.000	37.000
NSTO(WAA)	41.801	20.000	81.000	30.000
NSTO(WAA)	40.154	13.000	90.000	83.000
NSTO(WAA)	41.092	16.000	94.000	60.000
NSTO(WAA)	42.644	16.000	93.000	27.000
NSTO(WAA)	37.421	17.000	74.000	60.000
NSTO(WAA)	39.438	16.000	72.000	27.000
NSTO(WAA)	43.052	14.000	85.000	44.000
Mean	40.67			
Standard Dev.	2.06			
Expected Value	41.84			

Zone 1, Small Wastes, 0% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	42.323	22.500	173.00	574
Off Site_Ta	41.639	22.500	138.00	619
Off Site_Ta	41.549	22.500	138.00	619
Off Site_Ta	41.878	22.500	155.50	723
Off Site_Ta	41.643	22.500	127.50	639
Off Site_Ta	41.635	22.500	145.00	672
Off Site_Ta	42.441	22.500	173.00	714
Off Site_Ta	42.239	22.500	138.00	694
Off Site_Ta	42.607	22.500	148.50	749
Off Site_Ta	42.625	22.500	155.50	580
Mean	42.06			
Standard Dev.	0.43			
Expected Value	42.25			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	24.188	4.0000	47.000	38.000
NSTO(WAA)	25.705	9.0000	59.000	23.000
NSTO(WAA)	24.852	3.0000	74.000	16.000
NSTO(WAA)	30.329	13.000	72.000	27.000
NSTO(WAA)	26.096	6.0000	57.000	11.000
NSTO(WAA)	27.929	8.0000	61.000	21.000
NSTO(WAA)	30.036	9.0000	70.000	16.000
NSTO(WAA)	29.129	7.0000	83.000	13.000
NSTO(WAA)	31.508	7.0000	66.000	28.000
NSTO(WAA)	24.831	8.0000	57.000	25.000
Mean	27.46			
Standard Dev.	2.66			
Expected Value	27.34			

Zone 1, Large Wastes, 0% WEF

Results from 10 Runs, each 1500 time units (days) in length.

Data gathered over last 1000 time units.

For these runs, the resulting storage limit of 100 entities was exceeded. Therefore, the number of containers arriving each week was cut in half to avoid exceeding this constraint, and the resulting number of entities stored in the WAA represent one half of the actual inventory for these items. A close approximation to the true value can be obtained by multiplying the number of entities stored by two.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	36.158	19.000	145.00	697
Off Site_Ta	35.908	19.000	117.00	704
Off Site_Ta	35.651	19.000	117.00	726
Off Site_Ta	36.294	19.000	131.00	697
Off Site_Ta	36.318	19.000	159.00	657
Off Site_Ta	35.832	19.000	159.00	692
Off Site_Ta	35.713	19.000	148.50	783
Off Site_Ta	37.057	19.000	145.00	734
Off Site_Ta	36.104	19.000	127.50	682
Off Site_Ta	35.918	19.000	127.50	620
Mean	36.095			
Standard Dev.	0.408			
Expected Value	36.75			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	24.899	12.000	41.000	32.000
NSTO(WAA)	24.907	8.0000	53.000	22.000
NSTO(WAA)	25.873	8.0000	53.000	41.000
NSTO(WAA)	24.884	9.0000	47.000	26.000
NSTO(WAA)	23.964	7.0000	45.000	31.000
NSTO(WAA)	24.782	11.000	49.000	23.000
NSTO(WAA)	27.653	12.000	51.000	26.000
NSTO(WAA)	27.099	9.0000	49.000	19.000
NSTO(WAA)	24.642	9.0000	52.000	28.000
NSTO(WAA)	22.728	8.0000	47.000	47.000
Mean	25.14			
Standard Dev.	1.43			
Mean * 2	50.28			
Exp. Value / 2	25.54			
Expected Value	51.08			

Zone 1, Small Wastes, 25% WEF

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	34.953	8.5000	173.00	722
Off Site_Ta	34.427	8.5000	166.00	652
Off Site_Ta	34.915	8.5000	162.50	762
Off Site_Ta	34.403	8.5000	208.00	621
Off Site_Ta	33.819	8.5000	131.00	662
Off Site_Ta	34.329	8.5000	187.00	845
Off Site_Ta	33.403	8.5000	155.50	728
Off Site_Ta	32.891	8.5000	138.00	675
Off Site_Ta	34.363	8.5000	166.00	701
Off Site_Ta	35.112	8.5000	180.00	696
Mean	34.26			
Standard Dev.	0.71			
Expected Value	34.23			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	24.708	7.0000	68.000	17.000
NSTO(WAA)	22.126	5.0000	49.000	31.000
NSTO(WAA)	26.199	7.0000	74.000	20.000
NSTO(WAA)	22.000	5.0000	58.000	27.000
NSTO(WAA)	22.245	7.0000	55.000	19.000
NSTO(WAA)	29.462	9.0000	71.000	38.000
NSTO(WAA)	23.699	3.0000	52.000	16.000
NSTO(WAA)	24.803	5.0000	58.000	40.000
NSTO(WAA)	23.850	6.0000	60.000	26.000
NSTO(WAA)	22.020	5.0000	48.000	27.000
Mean	24.11			
Standard Dev.	2.36			
Expected Value	22.15			

Zone 1, Large Wastes, 25% WEF

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Once again, the resulting storage limit of 100 entities was exceeded. Therefore, the number of containers arriving each week was cut in half, and the results were treated as before (for the 0% WEF runs). It should be noted that the remaining runs would not have required this transformation of the arriving containers, since the maximum was below 50 (adjusted maximum below 100).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	29.692	8.5000	113.50	709
Off Site_Ta	28.722	8.5000	152.00	756
Off Site_Ta	31.167	8.5000	141.50	701
Off Site_Ta	29.395	8.5000	131.00	704
Off Site_Ta	30.465	8.5000	117.00	678
Off Site_Ta	29.857	8.5000	117.00	793
Off Site_Ta	29.747	8.5000	141.50	793
Off Site_Ta	29.331	8.5000	110.00	707
Off Site_Ta	30.335	8.5000	117.00	758
Off Site_Ta	28.749	8.5000	134.50	653
Mean	29.746			
Standard Dev.	0.76			
Expected Value	30.10			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	20.750	7.0000	38.000	16.000
NSTO(WAA)	21.436	10.000	53.000	18.000
NSTO(WAA)	21.916	7.0000	47.000	35.000
NSTO(WAA)	20.605	8.0000	44.000	26.000
NSTO(WAA)	20.574	6.0000	45.000	28.000
NSTO(WAA)	23.619	5.0000	47.000	27.000
NSTO(WAA)	23.886	10.000	47.000	40.000
NSTO(WAA)	20.832	9.0000	37.000	31.000
NSTO(WAA)	22.722	9.0000	44.000	26.000
NSTO(WAA)	18.531	4.0000	37.000	16.000
Mean	21.49			
Standard Dev.	1.61			
Mean * 2	42.98			
Exp. Value / 2	20.92			
Expected Value	41.84			

Zone 1, Small Wastes, 50% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	25.682	8.5000	117.00	607
Off Site_Ta	25.043	8.5000	138.00	739
Off Site_Ta	24.859	8.5000	124.00	703
Off Site_Ta	25.387	8.5000	155.50	577
Off Site_Ta	25.553	8.5000	173.00	658
Off Site_Ta	27.098	8.5000	194.00	736
Off Site_Ta	26.462	8.5000	183.50	651
Off Site_Ta	24.843	8.5000	134.50	669
Off Site_Ta	26.178	8.5000	148.50	687
Off Site_Ta	26.112	8.5000	145.00	775
Mean	25.72			
Standard Dev.	0.74			
Expected Value	26.20			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	15.591	2.0000	48.000	28.000
NSTO(WAA)	18.610	3.0000	48.000	22.000
NSTO(WAA)	17.954	5.0000	54.000	27.000
NSTO(WAA)	14.866	3.0000	47.000	41.000
NSTO(WAA)	16.864	3.0000	46.000	18.000
NSTO(WAA)	20.207	5.0000	48.000	23.000
NSTO(WAA)	17.283	3.0000	42.000	25.000
NSTO(WAA)	16.768	3.0000	44.000	31.000
NSTO(WAA)	17.768	3.0000	44.000	18.000
NSTO(WAA)	20.000	2.0000	46.000	5.0000
Mean	17.59			
Standard Dev.	1.72			
Expected Value	16.96			

Zone 1, Large Wastes, 50% WEF

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	21.935	8.5000	110.00	1239
Off Site_Ta	22.736	8.5000	155.50	1494
Off Site_Ta	23.274	8.5000	110.00	1360
Off Site_Ta	23.297	8.5000	131.00	1505
Off Site_Ta	23.037	8.5000	103.00	1388
Off Site_Ta	22.930	8.5000	134.50	1472
Off Site_Ta	23.480	8.5000	152.00	1492
Off Site_Ta	23.036	8.5000	180.00	1520
Off Site_Ta	23.456	8.5000	134.50	1357
Off Site_Ta	23.403	8.5000	152.00	1251
Mean	23.06			
Standard Dev.	0.46			
Expected Value	23.45			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	27.382	8.0000	59.000	54.000
NSTO(WAA)	33.442	7.0000	71.000	33.000
NSTO(WAA)	31.582	12.000	75.000	31.000
NSTO(WAA)	35.141	12.000	77.000	58.000
NSTO(WAA)	31.880	8.0000	69.000	29.000
NSTO(WAA)	33.503	13.000	90.000	33.000
NSTO(WAA)	34.965	13.000	79.000	27.000
NSTO(WAA)	34.419	13.000	77.000	42.000
NSTO(WAA)	31.622	6.0000	56.000	25.000
NSTO(WAA)	28.791	6.0000	78.000	46.000
Mean	32.27			
Standard Dev.	2.58			
Expected Value	32.60			

Zone 1, Small Wastes, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	17.592	8.5000	117.00	639
Off Site_Ta	17.584	8.5000	99.500	717
Off Site_Ta	17.290	8.5000	176.50	606
Off Site_Ta	17.709	8.5000	124.00	621
Off Site_Ta	17.758	8.5000	110.00	719
Off Site_Ta	18.348	8.5000	145.00	763
Off Site_Ta	17.990	8.5000	103.00	652
Off Site_Ta	18.454	8.5000	113.50	565
Off Site_Ta	17.952	8.5000	148.50	655
Off Site_Ta	18.320	8.5000	145.00	623
Mean	17.90			
Standard Dev.	0.38			
Expected Value	18.18			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	11.383	1.0000	33.000	18.000
NSTO(WAA)	12.708	1.0000	40.000	28.000
NSTO(WAA)	10.304	2.0000	40.000	15.000
NSTO(WAA)	10.986	1.0000	37.000	27.000
NSTO(WAA)	12.664	2.0000	36.000	8.0000
NSTO(WAA)	13.753	.00000	43.000	9.0000
NSTO(WAA)	11.753	2.0000	46.000	16.000
NSTO(WAA)	10.484	2.0000	36.000	9.0000
NSTO(WAA)	11.770	1.0000	43.000	5.0000
NSTO(WAA)	11.340	2.0000	39.000	27.000
Mean	11.71			
Standard Dev.	1.07			
Expected Value	11.76			

Zone 1, Large Wastes, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	16.439	8.5000	117.00	1568
Off Site_Ta	16.665	8.5000	155.50	1574
Off Site_Ta	15.719	8.5000	138.00	1422
Off Site_Ta	16.599	8.5000	113.50	1385
Off Site_Ta	16.622	8.5000	145.00	1294
Off Site_Ta	16.104	8.5000	110.00	1483
Off Site_Ta	16.256	8.5000	159.00	1499
Off Site_Ta	16.287	8.5000	99.500	1427
Off Site_Ta	15.957	8.5000	120.50	1338
Off Site_Ta	17.281	8.5000	113.50	1263
Mean	16.39			
Standard Dev.	0.44			
Expected Value	16.80			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	25.711	9.0000	79.000	51.000
NSTO(WAA)	26.168	9.0000	67.000	39.000
NSTO(WAA)	22.412	7.0000	63.000	20.000
NSTO(WAA)	22.970	6.0000	53.000	23.000
NSTO(WAA)	21.741	6.0000	53.000	18.000
NSTO(WAA)	23.782	7.0000	73.000	28.000
NSTO(WAA)	24.535	9.0000	62.000	58.000
NSTO(WAA)	23.069	3.0000	70.000	22.000
NSTO(WAA)	21.331	5.0000	81.000	46.000
NSTO(WAA)	21.711	6.0000	46.000	23.000
Mean	23.34			
Standard Dev.	1.69			
Expected Value	23.55			

Zone 2, Small Wastes, "Old" System.

Results for 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	31.614	15.500	127.50	927
Off Site_Ta	33.473	15.500	141.50	1080
Off Site_Ta	32.568	15.500	134.50	1031
Off Site_Ta	32.454	15.500	141.50	1059
Off Site_Ta	32.487	15.500	190.50	867
Off Site_Ta	32.547	15.500	127.50	1022
Off Site_Ta	32.602	15.500	120.50	986
Off Site_Ta	32.474	15.500	120.50	939
Off Site_Ta	31.812	15.500	106.50	1023
Off Site_Ta	32.547	15.500	148.50	951
Mean	32.46			
Standard Dev.	0.50			
Expected Value	32.65			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	29.256	11.000	57.000	42.000
NSTO(WAA)	36.107	12.000	64.000	46.000
NSTO(WAA)	33.290	12.000	62.000	37.000
NSTO(WAA)	34.271	11.000	63.000	38.000
NSTO(WAA)	28.006	14.000	55.000	38.000
NSTO(WAA)	33.120	14.000	81.000	30.000
NSTO(WAA)	32.434	16.000	64.000	38.000
NSTO(WAA)	30.445	13.000	55.000	44.000
NSTO(WAA)	31.925	11.000	66.000	24.000
NSTO(WAA)	30.867	13.000	63.000	33.000
Mean	31.97			
Standard Dev.	2.41			
Expected Value	32.04			

Zone 2, Large Wastes, "Old" System.

Results for 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	49.746	15.500	141.50	65
Off Site_Ta	49.119	15.500	162.50	71
Off Site_Ta	48.621	15.500	134.50	82
Off Site_Ta	47.092	15.500	113.50	76
Off Site_Ta	47.750	15.500	141.50	56
Off Site_Ta	44.881	15.500	120.50	76
Off Site_Ta	54.120	15.500	141.50	87
Off Site_Ta	47.000	15.500	141.50	76
Off Site_Ta	47.760	15.500	127.50	69
Off Site_Ta	46.200	15.500	120.50	70
Mean	48.23			
Standard Dev.	3.54			
Expected Value	47.94			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	3.4705	.00000	8.0000	6.0000
NSTO(WAA)	3.3975	.00000	10.000	2.0000
NSTO(WAA)	3.9890	.00000	9.0000	3.0000
NSTO(WAA)	3.5760	.00000	10.000	4.0000
NSTO(WAA)	2.5590	.00000	8.0000	1.0000
NSTO(WAA)	3.4780	.00000	8.0000	7.0000
NSTO(WAA)	4.6105	.00000	10.000	3.0000
NSTO(WAA)	3.6590	.00000	8.0000	4.0000
NSTO(WAA)	3.3815	1.0000	8.0000	5.0000
NSTO(WAA)	3.2580	.00000	8.0000	5.0000
Mean	3.54			
Standard Dev.	0.52			
Expected Value	3.56			

Zone 2, Small Wastes, 0% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	37.202	12.000	152.00	1026
Off Site_Ta	37.309	12.000	106.50	1021
Off Site_Ta	37.584	12.000	141.50	955
Off Site_Ta	37.709	12.000	148.50	1027
Off Site_Ta	37.935	12.000	187.00	946
Off Site_Ta	39.124	12.000	134.50	971
Off Site_Ta	38.077	12.000	138.00	1098
Off Site_Ta	38.072	15.500	152.00	955
Off Site_Ta	37.837	12.000	194.00	963
Off Site_Ta	38.641	12.000	127.50	1002
Mean	37.95			
Standard Dev.	0.58			
Expected Value	38.03			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	38.306	15.000	77.000	44.000
NSTO(WAA)	37.877	17.000	71.000	35.000
NSTO(WAA)	35.460	16.000	62.000	38.000
NSTO(WAA)	38.752	15.000	72.000	62.000
NSTO(WAA)	35.750	12.000	63.000	37.000
NSTO(WAA)	38.176	18.000	71.000	50.000
NSTO(WAA)	41.534	22.000	69.000	44.000
NSTO(WAA)	36.407	16.000	75.000	42.000
NSTO(WAA)	36.077	16.000	67.000	27.000
NSTO(WAA)	38.708	14.000	70.000	42.000
Mean	37.70			
Standard Dev.	1.84			
Expected Value	37.33			

Zone 2, Large Wastes, 0% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	47.122	19.000	131.00	86
Off Site_Ta	55.993	22.500	134.50	72
Off Site_Ta	51.973	22.500	138.00	76
Off Site_Ta	50.784	22.500	113.50	86
Off Site_Ta	52.955	22.500	155.50	67
Off Site_Ta	49.853	19.000	131.00	65
Off Site_Ta	53.716	22.500	127.50	74
Off Site_Ta	51.179	22.500	120.50	67
Off Site_Ta	52.065	22.500	176.50	76
Off Site_Ta	57.067	22.500	155.50	81
Mean	52.27			
Standard Dev.	2.89			
Expected Value	52.24			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	4.0125	.00000	10.000	5.0000
NSTO(WAA)	4.1685	1.0000	8.0000	4.0000
NSTO(WAA)	3.9960	1.0000	10.000	3.0000
NSTO(WAA)	4.4995	.00000	9.0000	8.0000
NSTO(WAA)	3.4890	.00000	10.000	2.0000
NSTO(WAA)	3.2445	.00000	7.0000	5.0000
NSTO(WAA)	3.7230	.00000	10.000	4.0000
NSTO(WAA)	3.4680	.00000	12.000	7.0000
NSTO(WAA)	3.8550	.00000	8.0000	2.0000
NSTO(WAA)	4.4135	.00000	10.000	3.0000
Mean	3.89			
Standard Dev.	0.41			
Expected Value	3.88			

Zone 2, Small Wastes, 25% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	31.409	8.5000	152.00	1034
Off Site_Ta	31.454	8.5000	173.00	1055
Off Site_Ta	32.049	8.5000	159.00	991
Off Site_Ta	32.153	8.5000	138.00	980
Off Site_Ta	31.830	8.5000	148.50	961
Off Site_Ta	32.349	8.5000	120.50	963
Off Site_Ta	31.437	8.5000	152.00	1046
Off Site_Ta	31.815	8.5000	131.00	1008
Off Site_Ta	30.670	8.5000	152.00	1044
Off Site_Ta	31.197	8.5000	120.50	967
Mean	31.64			
Standard Dev.	0.50			
Expected Value	31.99			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	32.457	17.000	55.000	43.000
NSTO(WAA)	33.424	13.000	59.000	43.000
NSTO(WAA)	31.670	13.000	55.000	26.000
NSTO(WAA)	31.264	12.000	59.000	37.000
NSTO(WAA)	30.245	9.0000	52.000	35.000
NSTO(WAA)	31.194	10.000	53.000	33.000
NSTO(WAA)	32.883	11.000	66.000	29.000
NSTO(WAA)	31.761	17.000	61.000	36.000
NSTO(WAA)	31.620	13.000	70.000	28.000
NSTO(WAA)	29.677	13.000	71.000	27.000
Mean	31.62			
Standard Dev.	1.13			
Expected Value	31.33			

Zone 2, Large Waste, 25% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	39.956	8.5000	131.00	81
Off Site_Ta	42.065	8.5000	127.50	61
Off Site_Ta	44.301	8.5000	127.50	83
Off Site_Ta	41.830	8.5000	113.50	65
Off Site_Ta	44.403	8.5000	155.50	62
Off Site_Ta	46.742	8.5000	131.00	68
Off Site_Ta	52.395	8.5000	141.50	72
Off Site_Ta	46.000	8.5000	131.00	63
Off Site_Ta	41.243	8.5000	176.50	76
Off Site_Ta	45.070	8.5000	152.00	78
Mean	44.40			
Standard Dev.	3.56			
Expected Value	44.97			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	3.1915	.00000	9.0000	3.0000
NSTO(WAA)	2.6770	.00000	7.0000	3.0000
NSTO(WAA)	3.5740	.00000	10.000	2.0000
NSTO(WAA)	2.7310	.00000	8.0000	4.0000
NSTO(WAA)	2.5540	.00000	9.0000	2.0000
NSTO(WAA)	3.0605	.00000	7.0000	5.0000
NSTO(WAA)	3.4305	.00000	10.000	2.0000
NSTO(WAA)	3.0890	.00000	12.000	8.0000
NSTO(WAA)	3.0545	.00000	8.0000	4.0000
NSTO(WAA)	3.5025	.00000	8.0000	6.0000
Mean	3.09			
Standard Dev.	0.35			
Expected Value	3.34			

Zone 2, Small Wastes, 50% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	24.883	8.5000	106.50	981
Off Site_Ta	25.658	8.5000	117.00	922
Off Site_Ta	24.813	8.5000	134.50	1038
Off Site_Ta	25.772	8.5000	148.50	1015
Off Site_Ta	24.875	8.5000	187.00	977
Off Site_Ta	26.616	8.5000	138.00	920
Off Site_Ta	25.681	8.5000	138.00	1022
Off Site_Ta	26.003	8.5000	113.50	988
Off Site_Ta	26.357	8.5000	194.00	998
Off Site_Ta	24.961	8.5000	134.50	1031
Mean	25.56			
Standard Dev.	0.65			
Expected Value	25.80			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	24.168	5.0000	50.000	20.000
NSTO(WAA)	23.212	10.000	52.000	20.000
NSTO(WAA)	25.723	11.000	47.000	37.000
NSTO(WAA)	26.127	9.0000	55.000	23.000
NSTO(WAA)	24.251	9.0000	45.000	27.000
NSTO(WAA)	24.452	9.0000	57.000	29.000
NSTO(WAA)	26.174	11.000	58.000	30.000
NSTO(WAA)	25.512	13.000	57.000	19.000
NSTO(WAA)	26.342	11.000	56.000	21.000
NSTO(WAA)	25.907	7.0000	61.000	37.000
Mean	25.19			
Standard Dev.	1.08			
Expected Value	25.32			

Zone 2, Large Wastes, 50% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	32.069	8.5000	131.00	79
Off Site_Ta	38.031	8.5000	127.50	64
Off Site_Ta	44.012	8.5000	134.50	82
Off Site_Ta	37.526	8.5000	113.50	75
Off Site_Ta	35.423	8.5000	155.50	65
Off Site_Ta	43.611	8.5000	155.50	63
Off Site_Ta	43.131	8.5000	141.50	57
Off Site_Ta	41.637	8.5000	131.00	62
Off Site_Ta	32.912	8.5000	127.50	80
Off Site_Ta	33.447	8.5000	152.00	86
Mean	38.18			
Standard Dev.	4.66			
Expected Value	37.69			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	2.4975	.00000	9.0000	1.0000
NSTO(WAA)	2.4680	.00000	7.0000	3.0000
NSTO(WAA)	3.3790	.00000	8.0000	1.0000
NSTO(WAA)	2.7775	.00000	8.0000	3.0000
NSTO(WAA)	2.1715	.00000	6.0000	2.0000
NSTO(WAA)	2.6605	.00000	8.0000	2.0000
NSTO(WAA)	2.2855	.00000	6.0000	4.0000
NSTO(WAA)	2.7375	.00000	11.000	8.0000
NSTO(WAA)	2.5730	.00000	8.0000	2.0000
NSTO(WAA)	2.7885	.00000	7.0000	3.0000
Mean	2.63			
Standard Dev.	0.33			
Expected Value	2.80			

Zone 2, Small Wastes, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	18.097	8.5000	106.50	1097
Off Site_Ta	19.130	8.5000	106.50	1022
Off Site_Ta	19.844	8.5000	134.50	957
Off Site_Ta	18.732	8.5000	117.00	942
Off Site_Ta	18.942	8.5000	103.00	971
Off Site_Ta	19.356	8.5000	134.50	1031
Off Site_Ta	19.706	8.5000	152.00	1001
Off Site_Ta	18.870	8.5000	106.50	998
Off Site_Ta	19.158	8.5000	194.00	1013
Off Site_Ta	19.440	8.5000	148.50	970
Mean	19.13			
Standard Dev.	0.51			
Expected Value	19.68			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	19.875	6.0000	44.000	28.000
NSTO(WAA)	19.160	6.0000	46.000	14.000
NSTO(WAA)	19.011	5.0000	42.000	26.000
NSTO(WAA)	17.809	4.0000	39.000	32.000
NSTO(WAA)	18.314	7.0000	47.000	23.000
NSTO(WAA)	19.733	6.0000	53.000	14.000
NSTO(WAA)	19.747	9.0000	49.000	22.000
NSTO(WAA)	18.713	4.0000	46.000	22.000
NSTO(WAA)	19.381	5.0000	65.000	30.000
NSTO(WAA)	18.884	7.0000	46.000	13.000
Mean	19.06			
Standard Dev.	0.66			
Expected Value	19.31			

Zone 2, Large Wastes, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	29.500	8.5000	131.00	77
Off Site_Ta	29.930	8.5000	190.50	65
Off Site_Ta	36.085	8.5000	127.50	76
Off Site_Ta	31.731	8.5000	127.50	69
Off Site_Ta	26.625	8.5000	106.50	56
Off Site_Ta	29.500	8.5000	82.000	65
Off Site_Ta	35.972	8.5000	141.50	73
Off Site_Ta	27.619	8.5000	120.50	67
Off Site_Ta	28.661	8.5000	127.50	71
Off Site_Ta	26.205	8.5000	117.00	85
Mean	30.18			
Standard Dev.	3.48			
Expected Value	30.41			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	2.2415	.00000	7.0000	1.0000
NSTO(WAA)	1.8795	.00000	6.0000	5.0000
NSTO(WAA)	2.6795	.00000	7.0000	2.0000
NSTO(WAA)	2.1745	.00000	7.0000	3.0000
NSTO(WAA)	1.4600	.00000	5.0000	1.0000
NSTO(WAA)	1.9725	.00000	7.0000	3.0000
NSTO(WAA)	2.3460	.00000	9.0000	1.0000
NSTO(WAA)	1.9225	.00000	8.0000	8.0000
NSTO(WAA)	2.0060	.00000	6.0000	1.0000
NSTO(WAA)	2.1815	.00000	6.0000	3.0000
Mean	2.09			
Standard Dev.	0.32			
Expected Value	2.26			

Zone 3, Small Wastes, "Old" System.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	38.074	17.500	129.50	494
Off Site_Ta	39.905	17.500	136.50	553
Off Site_Ta	36.073	17.500	122.50	574
Off Site_Ta	37.611	17.500	122.50	567
Off Site_Ta	37.570	17.500	192.50	557
Off Site_Ta	38.093	17.500	150.50	551
Off Site_Ta	38.033	17.500	171.50	555
Off Site_Ta	38.255	17.500	171.50	573
Off Site_Ta	38.596	17.500	178.50	583
Off Site_Ta	38.595	17.500	157.50	660
Mean	38.08			
Standard Dev.	0.97			
Expected Value	37.93			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	18.671	6.0000	41.000	24.000
NSTO(WAA)	21.444	7.0000	46.000	21.000
NSTO(WAA)	20.971	5.0000	48.000	34.000
NSTO(WAA)	21.396	7.0000	46.000	16.000
NSTO(WAA)	20.932	8.0000	44.000	32.000
NSTO(WAA)	21.375	5.0000	42.000	28.000
NSTO(WAA)	20.943	7.0000	51.000	15.000
NSTO(WAA)	21.760	6.0000	55.000	15.000
NSTO(WAA)	21.899	5.0000	61.000	11.000
NSTO(WAA)	25.508	8.0000	48.000	16.000
Mean	21.49			
Standard Dev.	1.67			
Expected Value	21.84			

Zone 3, Large Wastes, "Old" System.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	45.746	8.5000	134.50	243
Off Site_Ta	43.786	8.5000	120.50	171
Off Site_Ta	46.205	8.5000	113.50	251
Off Site_Ta	47.659	15.500	169.50	207
Off Site_Ta	48.229	8.5000	169.50	185
Off Site_Ta	44.435	8.5000	127.50	247
Off Site_Ta	45.158	8.5000	134.50	211
Off Site_Ta	44.993	8.5000	169.50	225
Off Site_Ta	46.554	8.5000	155.50	220
Off Site_Ta	45.182	8.5000	148.50	233
Mean	45.79			
Standard Dev.	1.39			
Expected Value	45.89			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	11.007	2.0000	25.000	11.000
NSTO(WAA)	7.6735	.00000	18.000	11.000
NSTO(WAA)	11.410	3.0000	26.000	5.0000
NSTO(WAA)	10.168	2.0000	25.000	14.000
NSTO(WAA)	9.0995	.00000	25.000	21.000
NSTO(WAA)	10.954	.00000	27.000	8.0000
NSTO(WAA)	9.6765	2.0000	18.000	8.0000
NSTO(WAA)	10.147	2.0000	28.000	17.000
NSTO(WAA)	9.8920	2.0000	32.000	3.0000
NSTO(WAA)	10.628	3.0000	27.000	9.0000
Mean	10.07			
Standard Dev.	1.09			
Expected Value	10.82			

Zone 3, Small Wastes, 0% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	45.592	22.500	131.00	537
Off Site_Ta	43.877	22.500	166.00	649
Off Site_Ta	44.716	22.500	169.50	472
Off Site_Ta	43.951	22.500	134.50	558
Off Site_Ta	45.715	22.500	180.00	545
Off Site_Ta	44.467	22.500	155.50	575
Off Site_Ta	45.119	22.500	162.50	603
Off Site_Ta	46.911	22.500	183.50	676
Off Site_Ta	45.676	22.500	187.00	537
Off Site_Ta	43.719	22.500	131.00	749
Mean	44.97			
Standard Dev.	1.02			
Expected Value	44.58			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	25.176	11.000	55.000	55.000
NSTO(WAA)	28.322	10.000	54.000	22.000
NSTO(WAA)	21.279	4.0000	55.000	21.000
NSTO(WAA)	24.693	5.0000	60.000	20.000
NSTO(WAA)	24.478	8.0000	47.000	8.0000
NSTO(WAA)	25.011	3.0000	68.000	20.000
NSTO(WAA)	27.219	8.0000	67.000	29.000
NSTO(WAA)	31.741	12.000	67.000	21.000
NSTO(WAA)	24.539	8.0000	48.000	25.000
NSTO(WAA)	32.798	8.0000	80.000	26.000
Mean	26.52			
Standard Dev.	3.55			
Expected Value	25.67			

Zone 3, Large Wastes, 0% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	50.105	12.000	117.00	213
Off Site_Ta	50.695	12.000	159.00	197
Off Site_Ta	51.202	12.000	131.00	274
Off Site_Ta	53.875	12.000	173.00	224
Off Site_Ta	50.562	8.5000	138.00	224
Off Site_Ta	50.513	12.000	131.00	268
Off Site_Ta	50.659	8.5000	148.50	198
Off Site_Ta	51.789	15.500	131.00	228
Off Site_Ta	52.972	8.5000	159.00	201
Off Site_Ta	51.913	12.000	148.50	203
Mean	51.43			
Standard Dev.	1.21			
Expected Value	51.11			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	11.046	1.0000	29.000	11.000
NSTO(WAA)	9.8270	2.0000	20.000	20.000
NSTO(WAA)	13.703	1.0000	26.000	10.000
NSTO(WAA)	12.191	2.0000	26.000	17.000
NSTO(WAA)	11.471	.00000	23.000	8.0000
NSTO(WAA)	13.678	2.0000	26.000	7.0000
NSTO(WAA)	10.424	1.0000	22.000	16.000
NSTO(WAA)	11.467	3.0000	24.000	3.0000
NSTO(WAA)	10.453	3.0000	24.000	7.0000
NSTO(WAA)	10.549	1.0000	23.000	10.000
Mean	11.48			
Standard Dev.	1.34			
Expected Value	12.05			

Zone 3, Small Wastes, 25% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	35.812	8.5000	162.50	647
Off Site_Ta	35.716	8.5000	131.00	514
Off Site_Ta	34.927	8.5000	169.50	561
Off Site_Ta	36.598	8.5000	117.00	535
Off Site_Ta	34.732	8.5000	180.00	592
Off Site_Ta	36.361	8.5000	141.50	507
Off Site_Ta	36.525	8.5000	183.50	558
Off Site_Ta	37.600	8.5000	169.50	604
Off Site_Ta	36.691	8.5000	145.00	602
Off Site_Ta	36.792	8.5000	169.50	598
Mean	36.18			
Standard Dev.	0.88			
Expected Value	35.97			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	23.577	7.0000	62.000	22.000
NSTO(WAA)	18.454	4.0000	41.000	16.000
NSTO(WAA)	19.491	6.0000	48.000	10.000
NSTO(WAA)	19.792	8.0000	35.000	14.000
NSTO(WAA)	20.295	7.0000	44.000	14.000
NSTO(WAA)	18.729	4.0000	40.000	26.000
NSTO(WAA)	20.420	5.0000	41.000	26.000
NSTO(WAA)	22.248	7.0000	55.000	16.000
NSTO(WAA)	22.164	4.0000	59.000	44.000
NSTO(WAA)	22.045	5.0000	46.000	24.000
Mean	20.72			
Standard Dev.	1.70			
Expected Value	20.71			

Zone 3, Large Wastes, 25% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	43.058	8.5000	117.00	230
Off Site_Ta	46.022	8.5000	166.00	222
Off Site_Ta	44.382	8.5000	138.00	242
Off Site_Ta	44.136	8.5000	159.00	242
Off Site_Ta	44.019	8.5000	204.50	229
Off Site_Ta	44.544	8.5000	131.00	238
Off Site_Ta	43.002	8.5000	124.00	246
Off Site_Ta	46.033	8.5000	124.00	181
Off Site_Ta	43.076	8.5000	113.50	223
Off Site_Ta	42.935	8.5000	148.50	242
Mean	44.12			
Standard Dev.	1.17			
Expected Value	42.54			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	9.9945	.00000	22.000	11.000
NSTO(WAA)	10.317	2.0000	22.000	6.0000
NSTO(WAA)	10.984	4.0000	25.000	11.000
NSTO(WAA)	10.740	2.0000	26.000	10.000
NSTO(WAA)	10.706	2.0000	21.000	13.000
NSTO(WAA)	10.695	1.0000	23.000	12.000
NSTO(WAA)	10.631	2.0000	21.000	9.0000
NSTO(WAA)	8.2580	1.0000	20.000	10.000
NSTO(WAA)	9.7970	1.0000	23.000	13.000
NSTO(WAA)	10.298	1.0000	23.000	11.000
Mean	10.24			
Standard Dev.	0.79			
Expected Value	10.03			

Zone 3, Small Wastes, 50% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	26.908	8.5000	131.00	609
Off Site_Ta	27.457	8.5000	145.00	598
Off Site_Ta	27.586	8.5000	138.00	492
Off Site_Ta	28.284	8.5000	141.50	674
Off Site_Ta	27.013	8.5000	180.00	570
Off Site_Ta	26.935	8.5000	141.50	606
Off Site_Ta	28.133	8.5000	176.50	566
Off Site_Ta	26.469	8.5000	134.50	582
Off Site_Ta	26.192	8.5000	148.50	745
Off Site_Ta	27.073	8.5000	141.50	603
Mean	27.205			
Standard Dev.	0.67			
Expected Value	27.36			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	16.310	3.0000	45.000	19.000
NSTO(WAA)	16.562	2.0000	43.000	19.000
NSTO(WAA)	13.932	3.0000	35.000	23.000
NSTO(WAA)	19.265	4.0000	46.000	25.000
NSTO(WAA)	15.570	3.0000	37.000	16.000
NSTO(WAA)	16.368	4.0000	46.000	24.000
NSTO(WAA)	15.762	3.0000	41.000	19.000
NSTO(WAA)	15.540	3.0000	34.000	27.000
NSTO(WAA)	19.900	4.0000	68.000	14.000
NSTO(WAA)	16.631	6.0000	37.000	19.000
Mean	16.58			
Standard Dev.	1.77			
Expected Value	15.75			

Zone 3, Large Wastes, 50% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	34.371	8.5000	117.00	273
Off Site_Ta	36.977	8.5000	159.00	220
Off Site_Ta	37.661	8.5000	194.00	211
Off Site_Ta	36.111	8.5000	159.00	234
Off Site_Ta	36.183	8.5000	138.00	221
Off Site_Ta	38.082	8.5000	134.50	219
Off Site_Ta	36.059	8.5000	131.00	254
Off Site_Ta	33.066	8.5000	106.50	211
Off Site_Ta	35.588	8.5000	113.50	215
Off Site_Ta	36.307	8.5000	148.50	218
Mean	36.04			
Standard Dev.	1.48			
Expected Value	33.97			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	9.2555	.00000	31.000	10.000
NSTO(WAA)	8.0490	1.0000	19.000	9.0000
NSTO(WAA)	7.7865	.00000	24.000	10.000
NSTO(WAA)	8.3200	.00000	25.000	7.0000
NSTO(WAA)	8.1835	1.0000	19.000	12.000
NSTO(WAA)	8.4590	1.0000	22.000	6.0000
NSTO(WAA)	9.3540	2.0000	24.000	6.0000
NSTO(WAA)	7.1820	.00000	16.000	9.0000
NSTO(WAA)	7.7605	1.0000	21.000	10.000
NSTO(WAA)	7.7160	2.0000	20.000	9.0000
Mean	8.21			
Standard Dev.	0.68			
Expected Value	8.01			

Zone 3, Small Wastes, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.
Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	19.144	8.5000	124.00	581
Off Site_Ta	18.930	8.5000	131.00	602
Off Site_Ta	17.857	8.5000	106.50	542
Off Site_Ta	17.292	8.5000	162.50	574
Off Site_Ta	18.466	8.5000	113.50	610
Off Site_Ta	19.555	8.5000	134.50	580
Off Site_Ta	20.101	8.5000	117.00	559
Off Site_Ta	17.769	8.5000	117.00	526
Off Site_Ta	18.837	8.5000	155.50	624
Off Site_Ta	17.353	8.5000	134.50	625
Mean	18.53			
Standard Dev.	0.95			
Expected Value	18.75			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	10.928	1.0000	44.000	6.0000
NSTO(WAA)	11.321	2.0000	40.000	11.000
NSTO(WAA)	10.091	.00000	37.000	14.000
NSTO(WAA)	10.021	.00000	39.000	9.0000
NSTO(WAA)	11.290	1.0000	36.000	7.0000
NSTO(WAA)	11.324	2.0000	35.000	13.000
NSTO(WAA)	11.116	2.0000	34.000	4.0000
NSTO(WAA)	9.5445	2.0000	31.000	14.000
NSTO(WAA)	11.794	2.0000	34.000	15.000
NSTO(WAA)	10.810	.00000	41.000	11.000
Mean	10.82			
Standard Dev.	0.71			
Expected Value	10.80			

Zone 3, Large Wastes, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	26.125	8.5000	96.000	252
Off Site_Ta	28.269	8.5000	176.50	236
Off Site_Ta	26.943	8.5000	117.00	204
Off Site_Ta	27.245	8.5000	159.00	236
Off Site_Ta	26.829	8.5000	99.500	232
Off Site_Ta	27.019	8.5000	127.50	230
Off Site_Ta	26.304	8.5000	120.50	253
Off Site_Ta	25.616	8.5000	134.50	265
Off Site_Ta	24.076	8.5000	124.00	242
Off Site_Ta	25.531	8.5000	106.50	209
Mean	26.40			
Standard Dev.	1.15			
Expected Value	25.39			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	6.6795	1.0000	16.000	12.000
NSTO(WAA)	6.7105	.00000	19.000	3.0000
NSTO(WAA)	5.4105	.00000	16.000	3.0000
NSTO(WAA)	6.5750	.00000	16.000	6.0000
NSTO(WAA)	6.3925	1.0000	22.000	12.000
NSTO(WAA)	6.0325	.00000	19.000	6.0000
NSTO(WAA)	6.5640	.00000	19.000	2.0000
NSTO(WAA)	7.0685	1.0000	17.000	9.0000
NSTO(WAA)	5.9045	1.0000	17.000	3.0000
NSTO(WAA)	5.4690	1.0000	20.000	6.0000
Mean	6.28			
Standard Dev.	0.55			
Expected Value	5.99			

Zone 4, Small Wastes, "Old" System.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	33.722	8.5000	162.50	1283
Off Site_Ta	32.205	8.5000	183.50	1353
Off Site_Ta	34.202	8.5000	120.50	1292
Off Site_Ta	33.306	8.5000	183.50	1267
Off Site_Ta	34.168	8.5000	197.50	1222
Off Site_Ta	33.774	8.5000	169.50	1284
Off Site_Ta	33.025	8.5000	148.50	1362
Off Site_Ta	34.737	8.5000	155.50	1346
Off Site_Ta	33.719	8.5000	120.50	1319
Off Site_Ta	33.242	8.5000	141.50	1313
Mean	33.61			
Standard Dev.	0.71			
Expected Value	33.09			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	43.386	23.000	72.000	53.000
NSTO(WAA)	43.372	14.000	80.000	45.000
NSTO(WAA)	43.995	22.000	69.000	36.000
NSTO(WAA)	41.890	20.000	77.000	37.000
NSTO(WAA)	41.138	16.000	67.000	38.000
NSTO(WAA)	43.350	8.0000	71.000	49.000
NSTO(WAA)	44.805	25.000	79.000	43.000
NSTO(WAA)	46.006	26.000	91.000	34.000
NSTO(WAA)	44.566	22.000	73.000	49.000
NSTO(WAA)	43.494	24.000	75.000	53.000
Mean	43.60			
Standard Dev.	1.39			
Exp. Value/2	44.175			
Mean * 2	47.20			
Expected Value	88.35			

Zone 4, Large Wastes, "Old" System.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	36.016	8.5000	127.50	782
Off Site_Ta	37.769	8.5000	169.50	805
Off Site_Ta	36.241	8.5000	162.50	839
Off Site_Ta	36.756	8.5000	148.50	791
Off Site_Ta	36.872	8.5000	183.50	771
Off Site_Ta	36.564	8.5000	141.50	863
Off Site_Ta	36.019	8.5000	155.50	801
Off Site_Ta	36.705	8.5000	127.50	750
Off Site_Ta	36.601	8.5000	148.50	828
Off Site_Ta	36.577	8.5000	134.50	815
Mean	36.61			
Standard Dev.	0.50			
Expected Value	36.49			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	27.761	16.000	45.000	25.000
NSTO(WAA)	30.387	17.000	50.000	25.000
NSTO(WAA)	30.328	17.000	48.000	23.000
NSTO(WAA)	28.965	18.000	47.000	25.000
NSTO(WAA)	28.116	17.000	45.000	17.000
NSTO(WAA)	31.499	19.000	51.000	29.000
NSTO(WAA)	29.174	10.000	45.000	22.000
NSTO(WAA)	27.397	15.000	48.000	27.000
NSTO(WAA)	30.092	14.000	47.000	26.000
NSTO(WAA)	29.626	15.000	50.000	26.000
Mean	29.33			
Standard Dev.	1.30			
Exp. Value/2	29.38			
Mean * 2	58.66			
Expected Value	58.75			

Zone 4, Small Wastes, "New" System, 0% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	39.595	12.000	169.50	1386
Off Site_Ta	38.940	12.000	166.00	1318
Off Site_Ta	38.821	8.5000	155.50	1375
Off Site_Ta	39.407	12.000	187.00	1211
Off Site_Ta	38.829	8.5000	201.00	1408
Off Site_Ta	38.756	8.5000	176.50	1328
Off Site_Ta	39.270	5.0000	148.50	1301
Off Site_Ta	39.785	12.000	162.50	1288
Off Site_Ta	39.133	5.0000	187.00	1252
Off Site_Ta	39.031	12.000	131.00	1387
Mean	39.12			
Standard Dev.	0.35			
Expected Value	38.65			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	54.723	30.000	87.000	42.000
NSTO(WAA)	51.016	22.000	89.000	34.000
NSTO(WAA)	53.693	22.000	79.000	46.000
NSTO(WAA)	47.579	22.000	83.000	43.000
NSTO(WAA)	54.603	33.000	81.000	40.000
NSTO(WAA)	51.163	24.000	89.000	44.000
NSTO(WAA)	51.037	23.000	93.000	62.000
NSTO(WAA)	51.401	29.000	81.000	53.000
NSTO(WAA)	48.716	31.000	72.000	55.000
NSTO(WAA)	53.923	22.000	87.000	39.000
Mean	51.79			
Standard Dev.	2.44			
Exp. Value / 2	51.60			
Mean * 2	103.58			
Expected Value	103.19			

Zone 4, Large Wastes, "New" System, 0% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	40.479	5.0000	148.50	818
Off Site_Ta	41.093	5.0000	218.50	765
Off Site_Ta	40.466	5.0000	176.50	826
Off Site_Ta	40.544	8.5000	148.50	778
Off Site_Ta	42.490	5.0000	204.50	752
Off Site_Ta	40.017	5.0000	110.00	806
Off Site_Ta	40.772	5.0000	141.50	784
Off Site_Ta	39.900	5.0000	141.50	844
Off Site_Ta	41.441	8.5000	152.00	782
Off Site_Ta	40.620	5.0000	134.50	823
Mean	40.78			
Standard Dev.	0.75			
Expected Value	41.04			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	33.098	17.000	51.000	44.000
NSTO(WAA)	31.561	16.000	54.000	38.000
NSTO(WAA)	33.183	19.000	47.000	22.000
NSTO(WAA)	31.488	17.000	50.000	38.000
NSTO(WAA)	32.001	15.000	51.000	43.000
NSTO(WAA)	32.112	18.000	47.000	30.000
NSTO(WAA)	32.206	17.000	48.000	39.000
NSTO(WAA)	33.869	19.000	54.000	39.000
NSTO(WAA)	32.242	13.000	52.000	28.000
NSTO(WAA)	33.230	15.000	54.000	34.000
Mean	32.50			
Standard Dev.	0.80			
Exp. Value / 2	33.01			
Mean * 2	65.00			
Expected Value	66.02			

Zone 4, Small Wastes, "New" System, 25% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	32.723	8.5000	148.50	1302
Off Site_Ta	32.469	5.0000	145.00	1294
Off Site_Ta	33.160	8.5000	141.50	1332
Off Site_Ta	32.811	8.5000	134.50	1413
Off Site_Ta	32.497	8.5000	166.00	1309
Off Site_Ta	33.195	5.0000	180.00	1326
Off Site_Ta	32.824	8.5000	187.00	1358
Off Site_Ta	32.669	8.5000	187.00	1452
Off Site_Ta	33.088	8.5000	127.50	1302
Mean	32.83			
Standard Dev.	0.27			
Expected Value	32.50			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	42.543	20.000	72.000	28.000
NSTO(WAA)	42.187	19.000	74.000	55.000
NSTO(WAA)	43.872	21.000	75.000	43.000
NSTO(WAA)	45.676	20.000	73.000	51.000
NSTO(WAA)	46.328	25.000	75.000	34.000
NSTO(WAA)	42.677	25.000	69.000	46.000
NSTO(WAA)	44.199	16.000	69.000	49.000
NSTO(WAA)	44.260	15.000	70.000	28.000
NSTO(WAA)	46.857	25.000	76.000	36.000
NSTO(WAA)	42.892	16.000	76.000	35.000
Mean	44.33			
Standard Dev.	1.65			
Exp. Value / 2	43.39			
Mean * 2	88.66			
Expected value	86.77			

Zone 4, Large Wastes, "New" System, 25% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	33.873	5.0000	148.50	741
Off Site_Ta	33.847	5.0000	127.50	805
Off Site_Ta	34.449	5.0000	124.00	828
Off Site_Ta	34.534	8.5000	134.50	789
Off Site_Ta	34.446	8.5000	113.50	818
Off Site_Ta	35.116	5.0000	148.50	787
Off Site_Ta	35.259	5.0000	155.50	770
Off Site_Ta	35.356	5.0000	141.50	814
Off Site_Ta	33.150	5.0000	120.50	813
Off Site_Ta	35.620	5.0000	134.50	812
Mean	34.57			
Standard Dev.	0.79			
Expected Value	34.74			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	24.840	11.000	38.000	30.000
NSTO(WAA)	27.390	10.000	49.000	32.000
NSTO(WAA)	28.725	14.000	46.000	27.000
NSTO(WAA)	26.885	10.000	40.000	21.000
NSTO(WAA)	28.081	14.000	44.000	20.000
NSTO(WAA)	27.275	12.000	44.000	40.000
NSTO(WAA)	27.177	15.000	44.000	29.000
NSTO(WAA)	28.412	14.000	44.000	21.000
NSTO(WAA)	27.193	16.000	43.000	33.000
NSTO(WAA)	29.180	13.000	46.000	33.000
Mean	27.52			
Standard Dev.	1.21			
Exp. Value / 2	27.94			
Mean * 2	55.04			
Expected Value	55.88			

Zone 4, Small Wastes, "New" System, 50% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	25.686	5.0000	124.00	1307
Off Site_Ta	26.239	8.5000	134.50	1259
Off Site_Ta	25.774	8.5000	176.50	1256
Off Site_Ta	25.487	8.5000	187.00	1311
Off Site_Ta	26.685	8.5000	152.00	1389
Off Site_Ta	27.122	8.5000	173.00	1331
Off Site_Ta	26.963	5.0000	152.00	1399
Off Site_Ta	26.598	8.5000	187.00	1356
Off Site_Ta	26.797	8.5000	127.50	1282
Off Site_Ta	25.470	8.5000	134.50	1354
Mean	26.28			
Standard Dev.	0.63			
Expected Value	26.53			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	33.695	12.000	60.000	33.000
NSTO(WAA)	32.791	13.000	56.000	18.000
NSTO(WAA)	32.747	9.0000	56.000	42.000
NSTO(WAA)	33.075	12.000	57.000	38.000
NSTO(WAA)	37.171	17.000	69.000	47.000
NSTO(WAA)	36.179	18.000	59.000	33.000
NSTO(WAA)	38.020	11.000	66.000	53.000
NSTO(WAA)	36.026	14.000	64.000	35.000
NSTO(WAA)	34.223	11.000	56.000	34.000
NSTO(WAA)	34.328	14.000	59.000	26.000
Mean	34.83			
Standard Dev.	1.90			
Exp. Value / 2	35.18			
Mean * 2	69.66			
Expected Value	70.35			

Zone 4, Large Wastes, "New" System, 50% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	26.317	5.0000	148.50	782
Off Site_Ta	27.495	5.0000	145.00	749
Off Site_Ta	27.328	5.0000	120.50	806
Off Site_Ta	27.967	5.0000	134.50	749
Off Site_Ta	28.087	5.0000	120.50	778
Off Site_Ta	28.730	5.0000	131.00	796
Off Site_Ta	28.226	5.0000	99.500	742
Off Site_Ta	27.352	5.0000	138.00	784
Off Site_Ta	26.767	5.0000	106.50	807
Off Site_Ta	27.874	5.0000	148.50	827
Mean	27.61			
Standard Dev.	0.71			
Expected Value	28.44			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	20.651	9.0000	36.000	22.000
NSTO(WAA)	20.648	8.0000	38.000	23.000
NSTO(WAA)	21.875	8.0000	39.000	21.000
NSTO(WAA)	21.009	8.0000	39.000	23.000
NSTO(WAA)	21.659	8.0000	36.000	30.000
NSTO(WAA)	22.588	9.0000	42.000	22.000
NSTO(WAA)	21.004	8.0000	37.000	31.000
NSTO(WAA)	21.806	9.0000	44.000	29.000
NSTO(WAA)	21.553	5.0000	36.000	20.000
NSTO(WAA)	23.297	13.000	41.000	21.000
Mean	21.61			
Standard Dev.	0.85			
Exp. Value / 2	22.87			
Mean * 2	43.22			
Expected Value	45.74			

Zone 4, Small Wastes, "New" System, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

Weekly container arrival rates were divided by two due to model constraint of 100 entities (student version).

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	20.243	5.0000	124.00	1306
Off Site_Ta	20.759	8.5000	134.50	1347
Off Site_Ta	19.571	8.5000	110.00	1293
Off Site_Ta	20.736	8.5000	120.50	1344
Off Site_Ta	20.133	8.5000	120.50	1229
Off Site_Ta	20.555	8.5000	159.00	1422
Off Site_Ta	20.359	8.5000	180.00	1429
Off Site_Ta	20.442	8.5000	124.00	1373
Off Site_Ta	20.503	8.5000	127.50	1271
Off Site_Ta	19.615	8.5000	106.50	1307
Mean	20.29			
Standard Dev.	0.42			
Expected Value	20.20			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	26.653	8.0000	53.000	25.000
NSTO(WAA)	27.819	13.000	62.000	32.000
NSTO(WAA)	25.093	6.0000	52.000	23.000
NSTO(WAA)	27.906	11.000	55.000	33.000
NSTO(WAA)	24.627	12.000	47.000	22.000
NSTO(WAA)	28.931	7.0000	61.000	20.000
NSTO(WAA)	28.859	9.0000	55.000	26.000
NSTO(WAA)	28.037	12.000	55.000	14.000
NSTO(WAA)	26.164	11.000	49.000	26.000
NSTO(WAA)	25.328	9.0000	49.000	25.000
Mean	26.94			
Standard Dev.	1.58			
Exp. Value / 2	26.97			
Mean * 2	53.88			
Expected Value	53.93			

Zone 4, Large Wastes, "New" System, 75% WEF.

Results from 10 Runs, each 1500 time units (days) in length.

Data Gathered over last 1000 time units.

TALLY VARIABLES

Identifier	Average	Minimum	Maximum	Observations
Off Site_Ta	21.475	5.0000	148.50	1459
Off Site_Ta	22.314	5.0000	113.50	1530
Off Site_Ta	21.318	5.0000	113.50	1612
Off Site_Ta	22.152	5.0000	155.50	1650
Off Site_Ta	21.456	5.0000	113.50	1553
Off Site_Ta	21.959	5.0000	152.00	1632
Off Site_Ta	21.580	5.0000	120.50	1644
Off Site_Ta	21.453	5.0000	222.00	1622
Off Site_Ta	22.047	5.0000	148.50	1486
Off Site_Ta	21.258	5.0000	152.00	1587
Mean	21.70			
Standard Dev.	0.38			
Expected Value	22.14			

DISCRETE-CHANGE VARIABLES

Identifier	Average	Minimum	Maximum	Final Value
NSTO(WAA)	31.456	12.000	60.000	32.000
NSTO(WAA)	34.345	17.000	63.000	42.000
NSTO(WAA)	34.008	10.000	60.000	32.000
NSTO(WAA)	36.595	9.0000	70.000	39.000
NSTO(WAA)	33.502	10.000	68.000	40.000
NSTO(WAA)	35.961	14.000	74.000	32.000
NSTO(WAA)	35.322	15.000	63.000	32.000
NSTO(WAA)	34.933	12.000	62.000	33.000
NSTO(WAA)	32.525	14.000	59.000	25.000
NSTO(WAA)	34.121	13.000	69.000	42.000
Mean	34.28			
Standard Dev.	1.54			
Expected Value	35.60			

Zone 1 Simulation Results:

Explanation of Table. The percentiles listed represent the percent of time that the peak weekly WAA load did not exceed the value below it for a given simulation. For example, during Run 1, out of 150 weeks sampled, there were 120 weeks (80%) during which the WAA did not exceed 216 5GCEs of storage space utilized. The Maximum observed value during that simulation run was a week during which the WAA held 292 5GCEs of material.

“Old” System.

Run	80%	90%	95%	99%	Max Observed
1	216	241	261	281	292
2	193	211	227	244	248
3	196	215	228	246	251
4	212	245	269	316	338
5	204	220	238	249	255
6	192	220	268	318	321
7	206	232	246	281	298
8	196	222	240	267	267
9	213	238	256	289	306
10	211	222	241	253	257
Average	203.90	226.60	247.40	274.40	283.30
Standard Dev.	9.04	11.61	15.38	27.53	32.09

The average of mean values for these percentiles are also given. This is the most useful information, reflecting a point estimate for storage capacity that would be utilized given a certain level of risk. For example, if the manager is willing to accept only very infrequent periods of time when he would exceed his storage capacity, then he would want to meet demand 95% of the time. To do this, he may want to ensure that his storage facility could accommodate approximately 247 5GCEs of waste. More conservatively, he may want to have about 269 5GCEs of storage capacity. For example, this could be (274) 5 gallon containers, or (60) 55 gallon drums and (94) 5 gallon carboys, or other

combinations. Since this model assumes that waste is being handled under the “old” system, no waste is pre-classified by a WEF.

There is no way to compute with certainty the maximum amount of waste that will be in storage. There is always some (however small) probability that a given capacity will be exceeded. This is true of any stochastic demand inventory problem. The above simulation demonstrates that the maximum amount ever achieved over the ten runs was 338 5GCEs of waste, but more runs of the simulation may achieve a value higher than this.

“New” System, Assumed 0% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	204	219	235	262	283
2	224	245	274	330	341
3	241	258	290	315	322
4	266	282	296	333	337
5	228	247	268	295	289
6	225	243	262	300	308
7	249	278	296	322	319
8	240	271	312	362	375
9	239	254	283	344	354
10	223	241	252	270	273
Average	233.9	253.8	276.8	313.3	320.1
Standard Dev.	16.99	19.18	23.23	31.76	32.66

“New” System, Assumed 25% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	182	209	228	250	283
2	219	230	246	281	341
3	206	221	234	246	322
4	213	229	244	271	337
5	218	243	266	292	289
6	201	225	248	299	308
7	200	224	246	283	319
8	214	221	254	274	375
9	214	235	263	320	354
10	211	231	244	270	273
Average	207.80	226.80	247.30	278.60	320.10
Standard Dev.	11.15	9.17	11.62	22.03	32.66

“New” System, Assumed 50% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	148	167	185	230	254
2	160	174	184	192	194
3	180	191	208	239	247
4	171	186	193	231	253
5	169	193	136	253	293
6	166	184	197	221	224
7	176	197	216	237	253
8	156	175	190	216	240
9	166	177	194	237	248
10	152	173	178	195	198
Average	164.40	181.70	188.10	225.10	240.40
Standard Dev.	10.33	9.94	21.50	19.48	29.04

“New” System, Assumed 75% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	122	133	138	153	156
2	128	146	163	252	264
3	133	150	158	177	225
4	139	146	158	191	201
5	139	160	176	233	230
6	127	139	158	178	192
7	129	137	153	177	193
8	124	139	164	193	210
9	145	163	179	207	220
10	141	168	182	230	253
Average	132.70	148.10	162.90	199.10	214.40
Standard Dev.	7.87	11.97	13.28	30.94	31.46

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Zone 2 Simulation Results.

“Old” System:

Run	80%	90%	95%	99%	MAX Observed
1	54	60	65	73	78
2	61	65	69	77	86
3	58	63	65	70	73
4	59	65	71	78	78
5	55	61	69	87	93
6	55	60	63	69	71
7	65	69	75	84	84
8	59	64	69	74	83
9	63	69	75	78	79
10	56	62	66	73	75
Average	58.50	63.80	68.70	76.30	80.00
Standard Dev.	3.66	3.29	4.11	5.77	6.62

“New” System, Assumed 0% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	69	81	85	95	100
2	63	69	77	85	86
3	61	63	68	74	76
4	66	69	74	87	91
5	59	64	68	83	84
6	62	70	76	92	97
7	68	72	76	82	83
8	61	63	74	82	84
9	62	70	75	84	91
10	65	73	79	89	93
Average	63.60	69.40	75.20	85.30	88.50
Standard Dev.	3.27	5.44	4.96	5.89	7.23

“New” System, Assumed 25% WEF.

Run	80%	90%	95%	99% MAX Observed	
1	53	58	61	81	83
2	52	59	65	81	83
3	56	60	66	74	76
4	55	62	67	74	79
5	53	55	58	64	68
6	51	55	57	59	64
7	55	64	68	74	83
8	56	60	64	82	83
9	55	63	65	69	77
10	56	59	62	65	67
Average	54.20	59.50	63.30	72.30	76.30
Standard Dev.	1.81	3.03	3.71	7.92	7.41

“New” System, Assumed 50% WEF.

Run	80%	90%	95%	99% MAX Observed	
1	46	51	53	58	59
2	45	50	54	59	60
3	46	51	56	58	58
4	48	56	59	63	64
5	44	48	52	60	63
6	43	50	54	63	66
7	48	53	58	68	69
8	48	54	61	68	69
9	46	52	56	64	74
10	46	55	63	73	76
Average	46.00	52.00	56.60	63.40	65.80
Standard Dev.	1.70	2.49	3.60	4.99	6.18

“New” System, Assumed 75% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	38	43	46	59	64
2	38	45	49	60	68
3	40	46	48	54	55
4	40	46	49	54	64
5	38	41	43	55	65
6	38	41	46	56	56
7	38	42	46	50	53
8	37	41	44	50	52
9	39	45	49	63	64
10	40	44	48	55	57
Average	38.60	43.40	46.80	55.60	59.80
Standard Dev.	1.07	2.07	2.15	4.14	5.77

Zone 3 Simulation Results.

“Old” System.

Run	80%	90%	95%	99%	MAX Observed
1	76	85	92	108	112
2	59	70	76	82	83
3	73	81	87	94	95
4	71	80	85	95	103
5	63	68	76	83	88
6	72	76	85	99	111
7	66	72	76	81	82
8	71	83	91	100	105
9	78	85	93	118	122
10	71	79	86	98	100
Average	70.00	77.90	84.70	95.80	100.10
Standard Dev.	5.79	6.15	6.63	11.79	13.19

“New” System, Assumed 0% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	75	88	96	108	109
2	78	84	89	105	108
3	79	85	89	98	100
4	70	79	83	90	95
5	82	90	94	98	99
6	69	76	81	95	101
7	81	98	105	123	133
8	98	104	110	118	126
9	75	84	90	95	95
10	88	98	110	120	134
Average	79.50	88.60	94.70	105.00	110.00
Standard Dev.	8.61	8.96	10.48	11.79	15.34

“New” System, Assumed 25% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	68	80	89	104	107
2	68	75	81	95	97
3	67	79	87	95	102
4	78	86	91	106	108
5	72	80	86	103	105
6	77	86	91	103	105
7	80	85	89	105	107
8	62	70	75	87	90
9	63	70	77	96	99
10	66	73	78	86	89
Average	70.10	78.40	84.40	98.00	100.90
Standard Dev.	6.35	6.20	6.10	7.35	6.98

“New” System, Assumed 50% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	58	65	70	85	87
2	57	63	70	78	79
3	55	60	66	73	75
4	64	72	80	95	98
5	58	67	72	80	81
6	55	60	65	70	73
7	64	77	86	96	98
8	58	65	73	86	86
9	62	69	75	84	93
10	70	80	91	115	118
Average	60.10	67.80	74.80	86.20	88.80
Standard Dev.	4.79	6.78	8.47	13.13	13.53

“New” System, Assumed 75% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	42	49	56	68	70
2	48	53	57	63	65
3	47	55	59	73	85
4	47	54	59	65	67
5	47	53	56	67	68
6	45	55	64	79	88
7	47	58	60	70	74
8	39	44	50	59	60
9	47	55	61	74	76
10	45	54	59	70	71
Average	45.40	53.00	58.10	68.80	72.40
Standard Dev.	2.84	3.89	3.73	5.77	8.71

Zone 4 Simulation Results.

“Old” System.

Run	80%	90%	95%	99%	MAX Observed
1	334	357	377	395	398
2	335	350	365	387	410
3	334	350	369	402	426
4	334	352	369	382	384
5	353	370	388	408	424
6	339	350	370	395	402
7	341	365	382	401	402
8	352	373	382	399	402
9	344	365	378	425	444
10	335	352	366	391	398
Average	340.10	358.40	374.60	398.50	409.00
Standard Dev.	7.37	9.01	7.86	12.00	17.49

“New” System, 0% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	380	402	422	440	448
2	382	401	410	420	440
3	379	400	417	450	452
4	367	383	400	421	424
5	374	395	404	416	418
6	370	382	397	419	448
7	376	396	415	424	430
8	357	371	383	405	408
9	348	363	377	397	400
10	371	381	397	413	416
Average	370.40	387.40	402.20	420.50	428.40
Standard Dev.	10.74	13.51	14.54	15.40	18.15

“New” System, 25% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	309	326	335	351	354
2	325	348	363	400	400
3	332	348	353	397	398
4	317	330	338	355	358
5	323	350	370	381	384
6	331	340	352	370	372
7	315	335	349	377	394
8	327	341	353	378	394
9	316	335	349	366	370
10	330	360	373	398	402
Average	322.50	341.30	353.50	377.30	382.60
Standard Dev.	7.86	10.32	12.33	17.37	17.86

“New” System, 50% WEF.

Run	80%	90%	95%	99%	MAX Observed
1	254	268	278	299	302
2	259	280	294	315	318
3	280	300	331	320	338
4	273	286	296	335	340
5	266	281	297	320	324
6	264	282	297	320	346
7	251	265	277	303	306
8	260	275	293	358	368
9	250	259	270	280	282
10	260	294	311	351	366
Average	261.70	279.00	294.40	320.10	329.00
Standard Dev.	9.49	12.75	17.64	23.53	27.88

“New” System, 75% WEF.

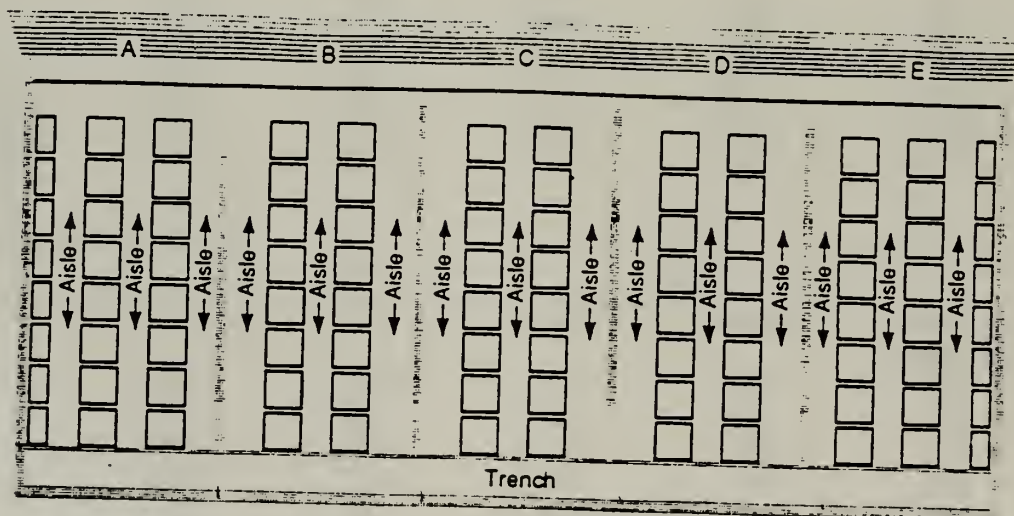
Run	80%	90%	95%	99%	MAX Observed
1	205	216	225	260	288
2	217	231	244	259	264
3	214	232	240	270	272
4	232	245	257	301	304
5	278	237	254	280	281
6	218	234	246	270	272
7	225	236	249	264	269
8	215	231	244	259	270
9	213	226	236	260	269
10	218	243	267	287	291
Average	223.50	233.10	246.20	271.00	278.00
Standard Dev.	20.45	8.28	11.64	14.21	12.68

APPENDIX D : EXCERPT FROM RCRA PART B PERMIT

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Table XIV.11-3. Sizes and Number of Containers in the Area 612-4 Receiving, Segregation, and Container Storage Unit

Container Size (gal)	Cell A or E Capacity (gal)	Allowed Number of Containers	Operating Number of Containers	Cell B, C, or D Capacity (gal)	Allowed Number of Containers	Operating Number of Containers
5	11,880	2,376	480	7,920	1,584	384
7	11,880	1,697	480	7,920	1,131	384
30	11,880	396	160	7,920	264	128
55	11,880	216	152	7,920	144	128
110	11,880	108	76	7,920	72	64
330	11,880	36	36	7,920	24	24
660	11,880	18	10	7,920	12	8
750	11,880	15	10	7,920	10	8
1,100	11,880	10	8	7,920	7	6
84 (ft ³)	11,880	18	18	7,920	12	12
112 (ft ³)	11,880	14	14	7,920	9	9
250 (ft ³)	11,880	6	6	7,920	4	4



APPENDIX E : AN INFINITE SERVER WASTE DISPOSAL MODEL

by

D. P. Gaver

P. A. Jacobs

D. McGoff

Let A_n be the amount of waste to arrive during week n . We will assume all waste arriving in a week arrives at the end of the week. Assume $\{A_n\}$ are iid. Let $S_{i,n}$ represent the time it takes to process the i^{th} unit of waste arriving in week n ; $S_{i,n}$ is in units of weeks. Assume $\{S_{i,n}; i = 1, \dots, A_n, n = 1, 2, \dots\}$ are iid random variables with $P\{S_{i,n} \leq t\} = G(t)$.

Assume waste that has finished being processed during week n is removed at the end of week n . Let L_n be the amount of waste present at the end of week n

$$L_n = \sum_{k=1}^n \sum_{i=1}^{A_k} I\{S_{i,k} > n - k\}$$

where

$$I(A) = \begin{cases} 1 & \text{if event } A \text{ occurs} \\ 0 & \text{otherwise} \end{cases}$$

1. Moments

$$E[L_n] = \sum_{k=1}^n E[A_k] [1 - G(n - k)].$$

Let $n \rightarrow \infty$

$$E[L_n] = E[A] E[S]$$

where S is a random variable with distribution function G and A is a random variable having the same distribution as A_n .

Further, since $\{A_n\}$ and $\{S_{i,k}\}$ are assumed independent

$$\begin{aligned} Var[L_n] &= \left[\sum_{k=1}^n \sum_{i=1}^{A_k} I\{S_{i,k} > n-k\} \right] \\ &= \sum_{k=1}^n Var \left[\sum_{i=1}^{A_k} I\{S_{i,k} > n-k\} \right] \\ &= \sum_{k=1}^n \left\{ E[A_k] Var[I\{S_{i,k} > n-k\}] + E[I\{S_{i,k} > n-k\}]^2 Var[A_k] \right\} \end{aligned}$$

$$Var[I\{S_{i,k} > n-k\}] = [1 - G(n-k)]G(n-k).$$

Hence

$$\begin{aligned} Var[L_n] &= E[A] \sum_{k=1}^n G(n-k)[1 - G(n-k)] + Var[A] \sum_{k=0}^n G(n-k)^2 \\ &= E[A] \sum_{k=1}^n G(n-k) + (Var[A] - E[A]) \sum_{k=1}^n G(n-k)^2. \end{aligned}$$

Let D_n be the amount of waste disposed of during week n

$$D_n = \sum_{k=1}^n \sum_{i=1}^{A_k} I\{n-k-1 < S_{i,k} \leq n-k\}.$$

Hence

$$\begin{aligned} E[D_n] &= \sum_{k=1}^n E[A_k] [G(n-k) - G(n-k-1)] \\ &= E[A] \sum_{k=1}^n [G(n-k) - G(n-k-1)] \\ &= E[A] G(n). \end{aligned}$$

Hence as $n \rightarrow \infty$

$$\lim_{n \rightarrow \infty} E[D_n] = E[A]$$

$$\begin{aligned} Var[D_n] &= \sum_{k=1}^n \left\{ E[A_k] Var[I\{n-k-1 < S_{i,k} \leq n-k\}] + Var[A_k] E[I\{n-k-1 < S_{i,k} \leq n-k\}]^2 \right\} \\ &= \sum_{k=1}^n \left\{ E[A_k] [G(n-k) - G(n-k-1)] [1 - [G(n-k) - G(n-k-1)]] + Var[A_k] [G(n-k) - G(n-k-1)]^2 \right\} \\ &= \sum_{k=1}^n E[A_k] [G(n-k) - G(n-k-1)] \\ &\quad + \sum_{k=1}^n (Var[A] - E[A]) [G(n-k) - G(n-k-1)]^2 \\ &= E[A]G(n) + \sum_{k=1}^n (Var[A] - E[A]) [G(n-k) - G(n-k-1)]^2 \end{aligned}$$

2. Generating Function

The (factorial moment) generating function of a random variable determines its distribution. The (factorial moment) generating function of a random variable X is

$$\varphi(\xi; X) = E[\xi^X]$$

for those values of ξ for which the expectation exists.

The generating function for the amount of waste present at the end of week n is

$$\begin{aligned} \varphi(\xi; L_n) &= E[\xi^{L_n}] \\ &= \prod_{k=1}^n E \left[\exp \left\{ \left(\sum_{i=1}^{A_k} I\{S_{i,k} > n-k\} \right) \ln \xi \right\} \right] \\ &= \prod_{k=1}^n E \left[[1G(n-k) + \xi[1 - G(n-k)]]^{A_k} \right] \\ &= \prod_{k=1}^n \varphi(G(n-k) + \xi[1 - G(n-k)]; A_k) \end{aligned}$$

An estimate of the generating function can be obtained by using the empirical distribution function \hat{G} and the empirical moment generating function of \tilde{A}_k .

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